Title

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Executive Summary

The California Air Resource Board (CARB) approved the Advanced Clean Cars Program in 2012, which requires the new light-duty vehicle (LDV) fleet to meet progressively more restrictive standards for fleet average greenhouse gas (GHG) emissions standards and to lower the fleet average emission of criteria pollutants. In 2016, Governor Brown signed the Senate Bill (SB) 32 establishing a new emission reduction target for California: reduce statewide GHG levels to 40% below 1990 levels by 2030. Subsequently, in 2017, CARB reaffirmed its commitment to the approved standards through 2025 and directed staff to begin work on rulemaking for GHG standards beyond 2025 to achieve the SB 32 targets. The SB 32 targets are expected to result in auto manufacturers accelerating the deployment of zero-emission vehicles (ZEVs). ZEVs include battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell electric vehicles (FCEVs).

Some critics assert that new vehicle regulations will not yield the expected emission benefits because the reduced operating costs often associated with lower GHG-emitting vehicles will result in greater usage of these vehicles. On the other hand, some recent studies have shown that ZEVs are being driven considerably fewer miles per year than are gasoline vehicles (*1*, *2*). This finding has brought into question the effectiveness of ZEVs in displacing gasoline vehicles. As ZEVs become an increasingly large fraction of new vehicle sales, a better understanding of plug-in electric vehicle (PEV) use will help refine the emissions impact assessments that depends on assumptions of average annual vehicle miles traveled (VMT). Additionally, understanding the usage of ZEVs within the context of all household vehicles is essential for accurately estimating the emission benefits of ZEV adoption.

In this study, we investigate BEVs and PHEVs, collectively referred to as plug-in electric vehicles (PEVs). Using statistical and econometric methods, we analyze the VMT of PEVs as part of household travel demand to understand how much PEVs are being used and the factors that influence their use in a household fleet. We use data from a repeat survey of PEV owners in California. The first survey was conducted in 2015–2018, shortly after the participants purchased their PEVs, and the repeat survey, of 4,925 PEV owners, was conducted in 2019. This approach allowed us to obtain two odometer readings leading to more accurate VMT measures. Exploratory analysis of the VMT estimated from the two odometer readings suggest that BEVs were driven on average 11,250 miles per year. Long-range BEVs (>200-mile electric range) travel around 13,000 miles per year while short-range BEVs (<120 miles of electric range) travel around 10,250 miles. PHEVs in the sample traveled on average approximately 12,000 miles. These results show that PEVs travel a similar number of miles per year as conventional vehicles.

These VMT estimates are compared to measures derived from other surveys of California PEV drivers (the California Vehicle Survey and the National Household Travel survey-California Add-on) and VMT estimates obtained from loggers installed in PEVs. The VMT estimates are similar across samples except for the NHTS data which shows lower PEV VMT, though the data contains a larger fraction of first-generation PEVs than the other surveys. Overall, VMT estimates from multiple surveys indicate that PEVs are driven a similar number of annual miles as gasoline vehicles (~10,800 miles). This finding has implications for emissions impact assessments of the PEV technology and predictive models of vehicular emissions. Of note, the analysis here compares annual mileage between PEVs and gasoline vehicles of similar model years (model years 2008 or later).

Households in the sample used for the econometric analysis have single-vehicle or multiple cars in their fleet (multi-vehicle households) such that a PEV is used in combination with conventional fuel vehicles. The results of the econometric models analyzing the integration of PEVs in household fleets show that, PEV VMT is correlated to factors such as population density, built environment, attitudes towards technology, and lifestyle preferences. These results are similar to factors correlated with VMT with conventional vehicles. Specific to PEVs, electric driving range and access to home charging infrastructure have a major influence on PEV VMT. Electric driving range is positively correlated with VMT. This suggests that longer range BEVs, which are the dominant BEV in the market, will displace more gasoline miles than shorter range BEVs were capable of. Note that from 2018–2020, BEVs with a range of <100 miles were only 2.4% of the PEV market, and these vehicles are being phased out. The correlation of home charging to VMT further highlights the importance of home charging access: home charging is the most influential charging location in the decision to buy a BEV, is the most frequently used (*3*), correlates with continuing PEV ownership after adoption (*4*), and enables more electric vehicle miles.

The econometric models and the exploratory analysis of VMT presented in this study offer a snapshot of the driving pattern of relatively newer PEVs (3.4 years is the average age of PEVs in the study sample). Analysis of how households may use PEVs versus conventional fuel vehicles over the long term is beyond the scope of this study. To assess the long-term environmental impact of promoting PEVs, policymakers and researchers will need to continue to collect data on how vehicle buyers respond to the evolution of the PEV technology along with other economic and built environment factors.

Overall, our results show that PEV VMT is correlated to similar factors as conventional vehicle VMT. EV range, household electricity price, and access to level 2 charging from home are additional variables correlated with PEV VMT. The results also show that BEVs and PHEVs appear to be viable as alternatives to conventional vehicles in terms of meeting the travel needs of households.

1 Introduction

In the United States, the transportation sector is the highest emitter of greenhouse gas (GHG) emissions, accounting for over 40% of the total emissions, with light-duty passenger vehicles being a major contributor (*5*). Light-duty vehicles also emit criteria pollutants contributing to poor air quality.[1] This has led policymakers both at the federal and state level to push for programs and regulations that encourage a transition from internal combustion engine vehicles (ICEVs) to battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), collectively referred to as plug-in electric vehicles (PEVs). California has a target of 5 million ZEVs (PEVs and Fuel Cell Electric Vehicles) on the road by 2030, and 100% of new vehicle sales being zero emission by 2035 (6). Accounting for well-to-wheel emissions and the 2017 California electric grid composition, these 5 million PEVs are expected to release 20.8 million fewer metric tons (MMT) of carbon dioxide equivalent (CO_2e) than the 5 million ICEVs (operating at an average of 24.3 miles per gallon [mpg]), which is 5% of total GHG emissions in California (*7*).[2] These vehicle emission estimates are based on average driving behavior and average fuel efficiency estimates, not accounting for heterogeneity in travel behavior or the possibility of a *rebound effect* (i.e., increased driving due to decreased vehicle operating costs per mile). In practice, the emission benefit of BEVs and PHEVs is related to how many gasoline miles are substituted by electric miles as well as where and when the PEVs are charged, and for PHEVs how many miles are driven using the electric motor vs. internal combustion engine.

In general, one may expect PEV adopters who trade off higher purchase prices for lower operating costs to maximize their electric miles (8). However, critics have argued that if lower operating costs lead to increased driving (i.e., the rebound effect), this will offset some or all the anticipated GHG emissions reductions. Studies of the rebound effect have mainly been in the context of ICEVs and conventional hybrid vehicles, with limited research in the context of PEVs (*9*, *10*). In addition to operating costs, vehicle miles traveled (VMT) at the household-level or a single vehicle-level can depend on other criteria. Past studies on household travel behavior have identified land-use diversity, built environment, lifestyle preferences, social interactions, and characteristics of the household fleet as factors influencing household vehicle use (*11*–*14*). For PEV owning households, additional factors could be correlated with VMT, such as: attributes of the PEV and the ICEV in the household, PEV driving range, and the need to plan a trip based on charger availability.

In this study we use data from a unique 'repeat survey' of PEV owners in California (with 4,925 survey respondents) administered in 2019 by the Plug-in-Hybrid and Electric Vehicle (PH&EV) Research Center at the University of California, Davis. The sample of PEV owners analyzed here had first been surveyed between 2015 and 2018, shortly after they first bought or leased their PEV. Using econometric methods, we investigate the role of factors that affect VMT, as identified in past studies in the context of PEVs (*9*–*14*). Further, we model PEV use in the household fleet over two points—at the times of the initial and repeat survey. The analysis is done for single- and multi-vehicles households separately, to study how PEVs are used in isolation and relative to gasoline cars. Such categorization of PEV owners by the number of household vehicles is important to understand how the ability (or its absence) of vehicle substitution impacts the integration of PEVs in a household fleet.

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[1] https://www.epa.gov/transportation-air-pollution-and-climate-change/smog-soot-and-local-air-pollution

[2] Considering the CAFE standards, the vehicle emission calculator of Alternative Fuel Data Center (AFDC), Department of Energy (DOE) uses 24.3 mpg as the conventional vehicle mpg (https://afdc.energy.gov/vehicles/electric_emissions_sources.html)

Estimating and comparing the use of BEVs and PHEVs to ICEVs in terms of total VMT is difficult for several reasons.[3] First, PEV technology is evolving at a fast pace. For example, 5 years ago, the range of a first-generation BEV on the market (Tesla excluded) was about 70–80 miles (e.g., the first-generation Nissan Leaf). Today, there are 13 BEV models available with ranges of more than 200 miles (e.g., Audi-etron, Chevrolet Bolt, Hyundai Kona Electric, Kia Niro Electric, Jaguar i-Pace, Tesla Model 3, second generation Nissan Leaf, etc.), and automakers have announced more upcoming models with even greater ranges. Owners of long-range rather than short-range BEVs may be more likely to use the vehicles for long commutes and for weekend trips. They could potentially be substituting more gasoline miles than a BEV with shorter range. Second, due to the short time on the market compared to ICEVs, there is uncertainty regarding how PEV use may change over time. PEV use can change as households adapt to the new technology, due to the diminishing "novelty effect," where a new product is used more because it is new and interesting, or the "sunk-cost fallacy," where an individual's initial product use is higher due to a high upfront expenditure on it (*15*, *16*). Third, is the issue of data availability and quality. The National Household Travel Survey (NHTS) 2017 California Add-on data only has 660 PEVs, with most of the BEVs in this sample being first-generation cars (e.g., the first-generation Nissan Leaf). The other public data source commonly used in transportation research, the California Vehicle Survey (CVS) 2019 administered by the California Energy Commission (CEC), has newer and longer range PEVs, such as the Tesla Model 3 or the Chevrolet Bolt in the sample, but includes only 550 PEVs. **Figure 1** shows how the data source used can impact VMT estimates. The figure includes NHTS data, CVS data, and two UC Davis data sources—a PEV owners survey in 2015–2019 and vehicle data recorders.

Focusing on vehicles of model year 2008 and later, PEV VMT estimates from the NHTS-2017 differ substantially from those calculated using the CVS-2019 data, UC Davis vehicle logger-based data from 369 PEVs tracked for one year, and the 'UC Davis eVMT survey' (Phase 1-Phase 4 (2015-2019)) data from 19,304 PEV owners.[4] The odometer data in the 'UC Davis eVMT Survey' is self-reported, as is the NHTS or the CVS data, but covers a wider range of PEV models and years. The UC Davis logger-based data comes from a smaller sample of PEVs, but in the absence of telematics data from the auto manufacturers, vehicle loggers are one of the most reliable sources of data on miles traveled, since they are not impacted by human error. Details on the composition of the sample of PEVs and ICEVs for the four data sources discussed here is in **Appendix A (Figure 7-Figure 14)**. As observed in **Figure 1**, the VMT estimates using the 2017 NHTS sample of PEVs are lower than other fuel types and lower than the PEV VMT estimates obtained from the other three sources. One explanation is that among the NHTS 2017 respondents sampled in 2016, a high percentage were first-generation BEVs (e.g., the Nissan Leaf with < 125 mile range) and PHEV owners with low electric range vehicles and early buyers of PEVs who are known to have a higher than average number of household vehicles (*17*). Compared to the NHTS, annual VMT estimates using data sources with newer vehicle models such as the Tesla Model 3 or Chevrolet Bolt show both PHEVs and BEVs travel a similar number of miles as gasoline vehicles.

Overall, the comparison of estimates from different data sources highlights the need for vehicle driving behavior data collected over a longer period of time, from a large sample of vehicle owners (as in the 'UC Davis eVMT Survey'), with a variety of PEVs (including short- and long-range vehicles).

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[3] For PHEVs, the focus is on total VMT. Separating eVMT (share of electric miles) from total VMT is beyond the scope of the study.

[4] Details on the survey methodology for the NHTS and CVS data with self-reported odometer readings is publicly available here and here respectively. Information on the data collected method for the two UC Davis surveys can be found here and here.

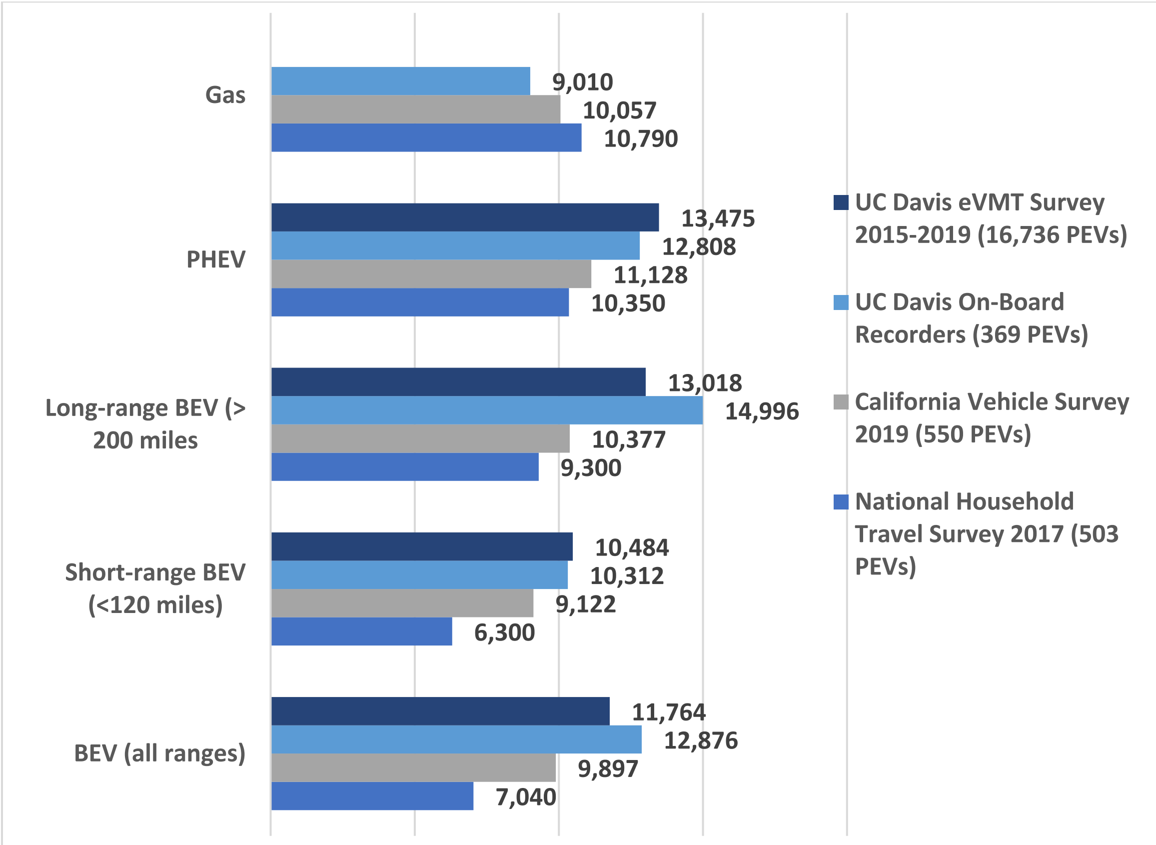

Figure 1: Comparison of VMT Estimates for California PEVs across surveys. The figure includes VMT estimates for gasoline vehicles, plug-in hybrid electric vehicles, short-range BEVs (<120 miles range), long-range BEVs (>200-mile range), and the average for all BEVs. For the average VMT estimation, the annual VMT for all powertrains was truncated at 75,000 miles.

Considering the GHG emission reduction targets and PEV adoption goals in California set by Senate Bill (SB) 32, ongoing policy efforts targeted towards auto manufacturers, and adoption trends, one can expect to see a rising share of PEVs in the vehicle fleet. As PEV penetration goes up, understanding the factors that influence the travel behavior of PEV drivers will help to refine the emissions impact assessment of these alternative fuel technology vehicles. These assessments depend on assumptions of average annual VMT, which can differ substantially based on the sample of vehicles analyzed, as demonstrated by **Figure 1**. A robust understanding of the travel behavior of PEV drivers is also required to evaluate the efficiency and incidence of pricing mechanisms such as the gas tax, mileage-based tax, or alternative funding mechanisms, such as a registration fee for PEVs. Finally, as the market for PEVs and the technology itself evolves, a robust estimate of VMT of PEVs will become important for assessing the impact on the energy/power sector.

The rest of the report is structured as follows. In Section **Error! Reference source not found.** we briefly review the literature related to VMT and the factors related to PEV usage. Next, in Section **Error! Reference source not found.** we give a description of the survey data and the methods used to analyze the impact of the determining factors on the VMT of PEVs. Findings from the econometric models are described in Section **Error! Reference source not found.**. Finally, we discuss the policy implications of the findings and conclusions in Section 5.

2 Literature Review

Exploring factors that impact household and vehicle-level VMT has been a topic of interest among researchers and policymakers for several decades, mainly due to the contribution of VMT to traffic congestion, emissions, and energy/fuel consumption. In the field of travel behavior, extensive research has been done on the impact of population density, built environment factors, land use characteristics, social network, spatial dependency, socio-demographics, and macroeconomic conditions on household and personal VMT (*11*, *12*, *18*, *19*). In addition to these factors, several studies have analyzed the impact of self-selection, namely the interaction between VMT and choice of residential location, neighborhood characteristics, or type of vehicle (*13*, *20*, *21*). In a recent study, Singh et al. (*22*) analyzed the relative contribution of all these factors on household VMT and found that while socio-demographic variables explain 33%, built environment 12%, and self-selection effects account for 11% of the household VMT, 44% of the household VMT remain unexplained, calling for further research on the topic.

In the economics literature, researchers have investigated consumer response to changes in fuel costs or fuel economy improvements (e.g., the rebound effect) in gasoline or hybrid vehicles. Controlling for macro-economic effects such as employment rate along with most of the factors mentioned above, researchers have estimated the fuel cost elasticity in terms of change in VMT at the regional-, household-, or vehicle-level (*9*, *23*–*26*). On average, the elasticity that represents the "rebound effect" is estimated to be 8-14% with considerable heterogeneity by vehicle type, vehicle age, and household income (*10*). A few studies have differentiated between the travel behavior of single- and multi-vehicle households and found that in the latter household type the potential for a rebound effect depends on the composition of the household fleet (*9*). In general, unlike single-vehicle households, a multi-vehicle household has the opportunity to respond to fuel prices by shifting miles to more fuel-efficient vehicles in their fleet and past research has found evidence of such behavioral response to an increase in gas price (*26*).

Fuel cost savings over the lifetime of the vehicle are generally a major motivation for the adoption of PEVs (*27*, *28*). Using interstate variation in gasoline and electricity rates, Sivak and Schoettle (*8*) observed that for all states in the US, the average annual fuel cost of driving a BEV with electricity efficiency of 33 kWh/100 miles is lower than an ICEV with an average fuel efficiency of 25 miles per gallon (*8*).[5] Considering the motivation to purchase a PEV and the elasticity of driving observed with fuel costs (*10*), one would expect that PEV owners would maximize the number of electric miles driven. However, there are contradictory findings in the literature in terms of PEV usage and VMT estimates. We could identify only a few studies that focus on PEV use and electric vehicle miles traveled. A recent study by Davis (*1*) using the 2017 National Household Travel Survey (NHTS) data finds that the average annual VMT of PEVs is 30% lower than other fuel type vehicles (*1*). On the other hand, analysis by Tal et al. (*29*) found that PEVs are being driven as much as gasoline cars, more so when long-range BEVs are taken into account. Nicholas and Tal (*30*) analyzed the factors that can influence the VMT of BEVs in a household and found that electric range, vehicle characteristics such as body type, access to charging at home, and vehicle sharing all play a role in how many miles a BEV has been driven annually (*30*). In addition to fuel cost-savings, PEV adoption is often motivated by symbolic attributes like self-environmental identity, personal environmental and technology-related beliefs, or attitude towards risk. Hasan and Simsekoglu (*14*) in their recent study addressed the effect of these psychological factors on post-purchase use of PEVs by single- and multi-vehicle households in Norway. The findings indicate that

[5] The authors considered the energy efficiency of the average vehicle for each powertrain type to compare their fuel costs.

PEV use (i.e., annual mileage) is more sensitive to economic factors in single-vehicle but more sensitive to perceived operating barriers in multi-vehicle households.

To date, there have been a limited number of studies on PEV use patterns, due to a lack of reliable data on the travel behavior of PEV owners (*31*). Although the 2017 NHTS and 2019 CVS data offer researchers the opportunity to fill this gap in the literature, it is essential to account for the characteristics of the sample of vehicles and households surveyed and their possible impact on VMT estimates. Early adopters of BEVs tend to have more vehicles in their household, be older, and be retired (*17*). All of these characteristics are correlated with lower VMT regardless of the vehicle technology owned. Also, the annual miles traveled estimate from the 2017 NHTS and the 2019 CVS publicly available data are based on single odometer readings (*29*). Using large-scale travel survey data such as the NHTS and the Residential Transportation Energy Consumption Survey (RTECS), past research has found that compared to dual readings single reported odometer readings can be unreliable, especially when the survey respondent is not the primary driver of the vehicle (*32*, *33*). The current study aims to address the limitations of prior PEV focused VMT studies by having a wider range of vehicle makes, models, and model years, and by using odometer readings reported by households at two time-points in the period of vehicle ownership to estimate VMT for the PEV. Compared to single odometer readings, dual odometer readings allow for more accurate VMT estimates as there are two data points to assess the validity of the self-reported odometer readings.

3 Data and Methodology

In this section, first, we describe the survey data analyzed for this study (section 3.1). In section 3.2, the econometric models used to investigate the factors influencing VMT of single- and multi-vehicle households with PEVs are explained.

3.1 Data description

In this study, we use a cohort survey of PEV owners in California administered by the authors in November 2019. Respondents of this "repeat survey" were recruited from a pool of respondents to a previous survey by the Plug-in Hybrid & Electric Vehicle (PH&EV) Research Center, conducted between 2015 and 2018 as part of the four phases of the UC Davis eVMT Survey. Respondents for the four phases of the UC Davis eVMT Survey were sampled from the pool of PEV buyers who had applied for the state rebate from the California Vehicle Rebate Project (CVRP) after they originally bought a PEV and were recruited by the California Air Resources Board (CARB). More than 25,000 PEV owners were surveyed in that initial survey. Of these, 15,000 gave consent to be re-contacted and were invited for the repeat survey in 2019. A total of 4,925 PEV owners responded to the repeat survey out of which 4,507 respondents reported a second odometer reading for the PEV they described when initially surveyed, herein referred to as 'Original PEV.' While 63% of the respondents (n=2604) had the same PEV in the two rounds of the survey, the remaining had ceased ownership of the PEV and either reduced their household fleet size, replaced the original PEV with another PEV, or replaced it with a gasoline vehicle. Households in the repeat survey sample may have purchased additional PEVs, but we focus on the original PEV since we obtained two odometer readings from that vehicle. When we surveyed PEV buyers in 2019, they had owned their original PEV for 2-7 years, with an average ownership period of 3 years and 5 months, compared to an average ownership of 1 year and 1 month in the first 4 surveys in 2015-2018 (considering the full sample of respondents of the repeat survey).

For the analysis of household-level PEV use, we merge the repeat survey data with the UC Davis eVMT Survey data. This gives us odometer readings and VMT estimates at two time-points. To estimate VMT for the respondents' PEV we consider two periods. First is the period from when the vehicle was purchased or leased to the date of the first survey (UC Davis eVMT Survey) conducted in 2015, 2016, 2017, and 2018; and second, the time from the first survey to the second survey (repeat survey). Using the strategy of other papers in the literature on "rebound effect" using odometer readings (*23*, *34*), we define original PEVs driving periods (in terms of months) as the unit of observation and use it to construct the dependent variable (VMT) for the econometric analysis. To account for the differences in ownership period, we normalize VMT to be in terms of annual VMT based on the number of months in each of the driving periods. Period 1 annual VMT estimates are calculated based on the odometer reading reported during the UC Davis eVMT Survey and the number of months between the vehicle purchase/lease date and the first survey completion date. We assume new vehicles were purchased with 0 miles on their odometers, though new cars typically have between 10-50 miles on their odometer. Period 2 annual VMT estimates are based on the odometer reading reported in the repeat survey and the number of months between the UC Davis eVMT Survey and repeat survey completion date or the date when the household ceased ownership of the PEV (e.g., because the lease ended, or the vehicle was sold or stolen, etc.). Below, **Figure 2** gives an illustration of the two time periods we consider in the VMT analysis. To address potential outliers, we truncate the data and drop observations where the VMT of the PEV was either 0 (PEV not used) or it was greater than 50,000 miles in one year (assuming higher annual miles are associated with likely reporting error or using the PEV for commercial purposes).

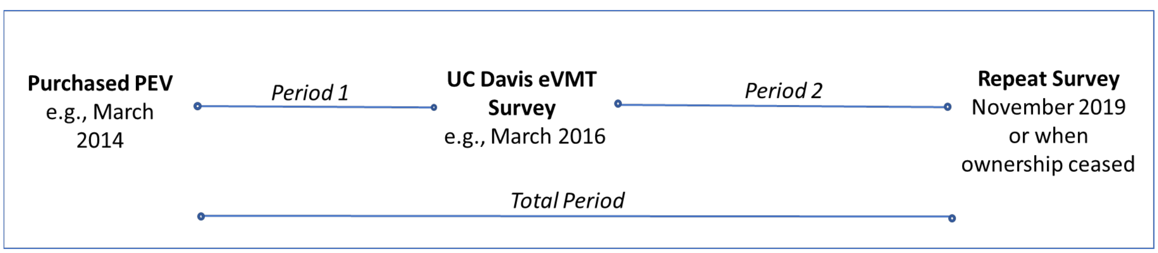

Figure 2: Timeline for the odometer readings and VMT estimates of the 'Original PEV': Example of a household purchasing a PEV in March 2014 and participating in the 2016 initial survey and then the 2019 repeat survey. Note: The initial surveys occurred between 2015-2018.

In addition to the odometer reading of the PEV tracked in the two rounds, households also report an estimate of the annual VMT (rather than reporting an odometer reading for every household vehicle) for other vehicles in their fleet, along with their attributes, such as the make, model, body type, and fuel/powertrain. The VMT estimates for other household vehicles are used to calculate the total household VMT of a multi-vehicle household. We use the same truncating rules for the VMT estimates of the other household vehicles.

The final dataset has VMT estimates for the 'Original PEV' of 4,125 households, all who responded to the repeat survey and remained in the sample after data cleaning.[6] In Period 1, there are 513 single-vehicle and 3,612 multi-vehicle households (2-vehicle=2,136; 3-vehicle=1,123; 4 or more=549). Among the

[6] We dropped those households that did not complete the repeat survey, i.e., where the number of pages completed were less than one standard deviation from the sample average (35 page) or completed it in less than 15 minutes (mean, 44 minutes and median, 21 minutes)

single-vehicle households, there are 225 BEVs and 288 PHEVs. Among the multi-vehicle households, we track 2,148 BEVs and 1,464 PHEVs. In Period 2, there are 742 single-vehicle households and 3,364 multi-vehicle households (2-vehicle=2,095; 3-vehicle=855, 4 or more=414). Some of the multi-vehicle households had multiple PEVs, but the analysis in this report focuses on the 'Original PEV.' The econometric model controls for the presence of other PEVs in the fleet of a multi-vehicle household, but the sub-group (households with multiple PEVs) is not analyzed separately. At the time of the repeat survey, 19 household had ceased ownership of the original PEV ('Original PEV') and did not have any other vehicle in the household.

Past studies exploring factors affecting household VMT have identified socio-demographic factors—such as household income, age of the respondent, characteristics of the household vehicle fleet, vehicle age (or ownership period in case the vehicle is bought new), and fuel price—as some of the potential drivers. These factors can also influence the VMT of PEVs. **Error! Reference source not found.** provides summary statistics for some of these key demographic and non-demographic variables for the two categories of households.

Table 1. Household demographics and vehicle characteristics for single-vehicle and multi-vehicle households.

Factors	Single-Vehicle Households (n=513)	Multi-vehicle Households (n=3,612)
% Purchased PEV	57%	55%
% Homeowners	66%	90%
% Detached Home	60%	77%
% Households in Income Categories		
Less than $100K (Base)	39%	12%
$100K-$199K	38%	41%
$200K-$299K	9%	20.4%
More than $300K	2.5%	13.5%
Decline to state	11.5%	12.6%
Avg. number of household members	1.58	2.89
Avg. months of ownership (PEV) [a]	40	42
Avg. months of ownership (BEV)	36	39
Avg. months of ownership (PHEV)	43	46
% with Level 2 charger @ Home	38%	53%
% Residing in an Urban core/district/neighborhood place type [b]	30%	11%
% Passenger cars / Original PEVs [c]	95%	94%
% Multiple PEV households		14.5%
Fleet composition:		
% with at least one Van [d, e]		9%
% with at least one SUV [d, e]		34%
% with at least one Pick-up Truck [d, e]		10%
Average age of non-PEVs [f]		9 years
Average fuel efficiency of non-PEVs		31 mpg

* The summary statistics are based on Period 1 data unless mentioned otherwise.

a. Total months of ownership considering Period 1 and Period 2 (Total Period)

b. Place type defined according to National Household Travel Survey 2017 classifications. https://nhts.ornl.gov/assets/DerivedVariablesV1.1.pdf

c. Passenger cars include hatchbacks, subcompact-, compact-, midsize-, large cars/sedans, small station wagons, and two-seater cars

d. Among the households with a BEV as the 'Original PEV,' 67% had at least one van, 60% had at least one SUV, and 50% had at least one pickup truck.
e. Fleet composition at the time of the UC Davis eVMT survey. Here, the focus is on 'Original PEV' that was most probably integrated into the household fleet as reported in the UC Davis eVMT survey
f. Age of non-PEVs = UC Davis eVMT Survey submission year minus model year.

3.2 Model Description

In this section we describe the econometric models used to analyze the relationship between VMT of PEVs and its determining factors and the model to evaluate PEV use over time in single- and multi-vehicle households. Following past studies on vehicle use at the household-level, the single- and multi-households are analyzed separately (*9*, *19*). Two separate models are required to estimate VMT of the 'Original PEV' in these two types of households, because, for single-vehicle households the VMT of the 'Original PEV' is the same as the household VMT, while for multi-vehicle households, the VMT of the PEV is a fraction of the household VMT. As a result, in addition to the usual determining factors such as cost and sociodemographic characteristics, the model for multi-vehicle households needs to account for the effect of the attributes of other household vehicles (e.g., fuel efficiency, passenger/cargo capacity, and vehicle age) on the PEV VMT. Moreover, in the case of multi-vehicle households, a separate estimation technique is required to account for the relationship between the VMT of PEVs and total household VMT.

The econometric models estimated here focus on the Original PEV. For the econometric models investigating the factors influencing VMT of the Original PEV, we use the odometer readings, household sociodemographic, and fleet characteristics from Period 1, offering a cross-sectional analysis of PEV usage in a household fleet. This choice of these Period 1 data is primarily because some household characteristics—such as number of household members, access to home charger or home ownership—may have changed between the two surveys, and neither of the surveys have data on any household-level dynamics. The second odometer reading from the repeat survey is used to check for outliers in the Period 1 VMT estimates, assess the validity of self-reported odometer readings, and clean the data accordingly before analysis.

Along with sociodemographic characteristics and built environment factors, vehicle age also affects miles traveled with a vehicle. For example, studies suggest that the VMT of gasoline vehicles decreases with vehicle age (*35*, *36*). To have a better understanding of how VMT of a PEV in a household fleet may change over time and the factors that can influence it, we use the odometer readings from the two periods (Period 1 and Period 2) to estimate a mixed model as described below. Vehicle age is represented here by the months of ownership since the purchase date. Though generally ownership period and vehicle age may not be the same (e.g., when the vehicle is bought used), in this project we only consider PEVs that were purchased new and we have the data needed to calculate precisely the number of months of ownership.

3.2.1 Factors Affecting the VMT of Single-Vehicle Households

To analyze the factors related to PEV VMT of single-vehicle households, we first estimate an ordinary least square (OLS) regression model. The model controls for the influence of economic factors such as cost of charging at home, built environment factors, sociodemographic characteristics, lifestyle preferences, and seasonal variation in driving behavior on total household VMT (total VMT of the Original PEV). The list of explanatory variables included in the model for single-vehicle households is given in **Error! Reference source not found.**.

Cost of charging at home is represented here by electricity price at home ($/kWh). The data on household electricity rate ($/kWh) is based on the electricity rate plan and utility name reported by the survey respondents.[7] The extent of use of workplace and public charging also affects the cost of driving a PEV and thereby can impact VMT. However, due to the absence of data on the dollar-value or cost of charging at workplace or public chargers, we include only the residential electricity rate. Focusing solely on residential electricity rate can lead to underestimation (if dependence on public charging is high) or overestimation (if there is access to free non-home charging) of the effect of cost on PEV use. But we assume that the potential bias is small, because home continues to be the most commonly used charging location, and the residential electricity rate has a major influence on the operating cost of the 'Original PEV' (*3*, *37*).

In terms of household characteristics, households with higher income and more members may have a higher dependency on auto travel, leading to more VMT. Homeownership and living in a detached home can be considered an indicator of potential access to charging opportunities at home. Access to Level 2 charging at home is generally an important driver of charging behavior among PEV owners (*37*) and availability of charging capability at home may also lead to greater vehicle use. The dummy variable corresponding to the purchase/lease decision controls for the effect of the mileage limitations of leased PEVs; households have to pay a penalty if the miles are exceeded or need to pay to increase the mileage limit of their lease. Since the number of miles traveled with a PEV in a household can depend on how many drivers share the vehicle, the model controls for the relation between vehicle sharing (dummy) and VMT. There is no specific prior hypothesis for the respondent characteristics, but it is important to control for its effects on VMT as travel needs may vary by gender and age groups. All the variables related to household and respondent characteristics are derived from the UC Davis eVMT survey.

The model controls for the following built environment factors: population density, neighborhood walkability index, and the type of neighborhood as households in suburban locations tend to have a higher VMT than those close to urban centers. Data for the built environment factors are derived from the EPA Smart Mapping Tool.

In addition to land-use characteristics and neighborhood attributes, the choice of powertrain can depend on a household's lifestyle and attitude towards technology or environment. Therefore, using the responses to Likert scale questions in the repeat survey on lifestyle preferences and attitudes towards technology and environment, we conduct a principal component analysis with varimax rotation to identify the dimensional structure of the scale measuring different perceived attributes related to vehicle/PEV use. Kaiser's "eigenvalue >1" criterion and scree plot were used to determine the number of dimensions. The eight principal components referred to as *lifestyle preference* variables are:

- Likes sub-urban living
- Has a stressful commute
- Likes outdoor living (e.g., outdoor sports and activities)
- Is pro-technology
- Dislikes exercise
- Likes store shopping
- Needs a car for family needs

[7] For households reporting tiered rate structure, we assume that they are on Tier II rates offered by SDG&E, SCE, and PG&E (or the rate of the highest tier for other utilities). For households, mentioning time-of-use we consider the lowest rate if they also mention that they mostly do overnight charging. Otherwise, we take the average of the rates for different time slots.

- Utilizes travel time

Survey respondents were also asked to evaluate their PEV based on the following factors: safety, comfort, refueling/recharging costs, performance, environmental impacts, vehicle purchase price (including rebates, discounts, etc.), reliability, electric driving range, convenience of charging, and driving assistance features (e.g. cruise control, automatic braking lane assist, etc.). Using a similar factor analysis method, these ten statements were reduced to the following two principal components:

- Concerned about safety, reliability, and environment
- Concerned about the range and charger availability

The above two component scores from the factor analyses were used in the models as independent variables controlling for the effect of general opinion towards PEV technology and the associated charging infrastructure on vehicle use *(Attitude towards PEV technology)*.

Considering the vehicle characteristics, PEV use can depend on the electric range of the vehicle. Thereby, in the model, we control for the effect of vehicle's electric range on VMT. Data on PEV attributes such as the electric range is obtained from www.fueleconomy.gov. As range anxiety is an issue associated with BEVs, we control for the effect of the powertrain on VMT by including a dummy variable where 1=BEV and 0=PHEV in the model. Additionally we add a dummy to control for the effect of Tesla on VMT, based on the hypothesis that a Tesla would be driven more than other BEVs because it offers a higher level of automation in driving (*38*) and costs more, thereby affect VMT through the sunk-cost fallacy. Finally, to control for seasonal variation in travel behavior, the model controls for the number of summer months in the period between purchase/lease and completion of the first survey. As households tend to take longer trips during summer, we hypothesize that PEVs with more summer months in the ownership period may have higher annual VMT. We also control for the number of months in the ownership period to account for the age of the vehicle and the potential "novelty effect" on vehicle use (since all the vehicles in the sample were purchase/leased new).

Standard linear regression techniques such as OLS summarize the average relationship between a set of explanatory variables and an outcome variable based on the conditional mean function $E(y|x)$. However, households may display considerable variation in their travel needs resulting in a skewed VMT distribution (*39*). To capture the heterogeneity in driving behavior, we estimate a quantile regression (QR) model. Unlike OLS regression, the QR model offers a richer characterization of data, allowing us to consider the impact of explanatory factors on the entire distribution of household VMT and not just the conditional mean. The standard linear conditional quantile regression for the q^{th} quantile is:

$$Q_q(y_i|x_i) = x_i'\beta_q \text{ , where } i \text{ = represents the Original PEV of household } 'i' \quad (1)$$

The q^{th} quantile regression estimate $\widehat{\beta_q}$ minimizes over β_q the objective function

$$Q(\beta_q) = \sum_{i:\, y_i > x_i'\beta}^{N} q\left|y_i - x_i'\beta_q\right| + \sum_{i: y_i < x_i'\beta}^{N} (1-q)\left|y_i - x_i'\beta_q\right| \ , \quad (2)$$

where, $0<q<1$ and estimation set at $q_{0.5}$ gives the conditional median estimator that minimizes $\sum_i |y_i - x_i'\beta_{0.5}|$

For analysis of household VMT/VMT of PEVs here, we consider the QR estimates for 10th, 25th, 50th, 75th, and 90th quantile. The OLS and quantile regression models use the same set of explanatory variables given in Table 2.

Table 2: Explanatory Variables for Model Estimating VMT in Single-Vehicle Households.

PEV characteristics	• Residential electricity rate ($/kWh) • Electric range of PEV • PEV is shared or not (No=1) • Purchase or leased (Purchase=1) • BEV or not (Yes=1) • Tesla or not (Yes=1)
Built environment	• Population density • National Walkability Index • Sub-urban/Urban/Rural
Household characteristics	• Home ownership (Yes=1) • Dwelling type (Detached home=1) • Charging opportunity (Level 2) (Yes=1) • Household size • Annual household income
Respondent characteristics	• Age • Gender (Male=1) • Lifestyle preference • Attitude toward PEV technology
Other factors related to PEV use	• Access to paid public charging or not (Yes=1) • Number of months PEV owned and proportion of summer months • Frequency of PEV use for commute*

*Since the commute miles would have been endogenous with total 'Original PEV' VMT and household VMT we include frequency of commute to control for the effect of using a vehicle for commute on VMT

3.2.2 Factors Affecting the VMT of Multi-Vehicle Households

For multi-vehicle households, to account for the inter-relationship between total household VMT and that of the surveyed PEV, we use a multivariate linear regression method: seemingly unrelated regression (SUR) model. The SUR model consists of 'm' linear regression equations for N individuals with the errors contemporaneously correlated across equations for a given individual but uncorrelated across individuals. The jth equation for the ith individual is given as:

$$y_{ij} = x'_{ij}\beta_j + u_{ij} \text{ ; } j=1, 2\ldots m \text{ and } i=1, 2\ldots N \quad (3)$$

Stacking the 'm' linear regression equations for ith individual (Original PEV of household 'i') gives the SUR model

$$\begin{bmatrix} y_1 \\ y_2 \\ \cdot \\ \cdot \\ y_m \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & & \cdots & X_m \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \cdot \\ \beta_m \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ \cdot \\ u_m \end{bmatrix} \quad \text{with } E\left(u_{ij}u_{ij'}|X\right) = \sigma_{jj'}, \, and \; \sigma_{jj'} \neq 0 \; where \; j \neq j' \quad (4)$$

The error terms are assumed to have zero mean, independent across individuals, and homoscedastic.

In our application of the SUR model here, the two dependent variables are *Total household VMT* and the *Share of PEV in household VMT* in Period 1 of the survey. There are two equations in the system (j=2) for each household Original PEV 'i' with the error of the two equations contemporaneously correlated for each household but independent across households. The explanatory variables for the two equations in the SUR model are given in Table 3. The set of variables for the two equations were decided based on our review of the literature focusing on household VMT and studies on PEV driving/charging behavior.

Table 3: Explanatory Variables included in the SUR Model.

Equation 1: Total Household VMT

Household vehicle characteristics	• Household has at least one van, SUV, or truck (Yes=1) • Average age of the household fleet • Average cost of driving non-PEVs (1/Average MPG of non-PEVs) × Gasoline price ($/gallon) • More than one PEV or not (Yes=1)
Household Characteristics	• Household size • Number of vehicles (total) • Household income (annual) • Lifestyle preferences (component scores)
Built environment	• National walkability index • Total population density • Sub-urban/Urban/Rural

Equation 2: Share of PEV in Household VMT

PEV characteristics	• Electric range (EPA range) • BEV or not (BEV=1) • Ratio of PEV to the age of the second most used vehicle (based on reported annual VMT) • Vehicle shared or not (shared=1) • Leased/purchased (purchased=1) • Frequency of commute*
Household & Respondent characteristics	• Charging opportunity at home (Yes=1) • Electricity rate paid (at home) • Number of vehicles (total) • Homeownership & dwelling type • Paid public charging or not (Yes=1) • Attitude related to PEV technology (component scores) • Respondent age and gender
Household vehicle characteristics	• Household has at least one van, SUV, or truck (Yes=1) • More than one PEV or not (Yes=1) • Average cost of driving non-PEVs (1/Average MPG of non-PEVs) ×Gasoline price ($/gallon)
Built environment	• Sub-urban/Urban/Rural

*Since the commute miles would have been endogenous with total 'Original PEV' VMT and household VMT we include frequency of commute to control for the effect of using a vehicle for commute on VMT

The hypothesis associated with the explanatory variables included in the OLS or QR model remains the same except now factors such as access to Level 2 charger or attitude towards PEV technology are expected to influence the share of VMT rather than the total household VMT. In general, depending on the equation in which a variable is included, the variable is either interpreted as a factor influencing total household VMT or the share of PEV in total VMT.

In the case of multi-vehicle households, attributes of the other vehicles in the household fleet can affect the use of a PEV. In multi-vehicle households, PEVs may have a lower share in the total household VMT than the other vehicles, particularly if the PEV has a short electric range. However, if the other vehicles in the fleet have lower fuel efficiency and the cost of driving the non-PEVs is high, or they are much older than the PEV, the share of VMT of the PEV can be high. Considering fleet composition, households with a truck, van, or SUV may have certain travel needs that can also impact the use of the PEV in the household. Therefore, in the SUR model, we include dummies controlling for household fleet composition. Finally, as in the case of single-vehicle households, we consider the effect of electricity cost on the share of PEV in total household VMT. A major concern with using fuel price as an independent variable to explain VMT is endogeneity (*9*). We assume that the choice of electricity rate structure is made after vehicle purchase based on rate offerings of the utility service provider, ability to charge at home, propensity to use vehicle timer to adjust to a special rate structure, independent of the VMT decision. Moreover, currently the main objective of the EV-special rates offered by utilities is to shift electricity demand for vehicle charging from peak to off-peak periods of demand at the grid-level. As the demand for electricity due to vehicle charging at home is still a minor share in the total residential demand for electricity in California, it is unlikely that currently the VMT of PEVs influence the residential electricity rate structures.

While we expect the rich set of control variables included in the models for the two categories of households to address a variety of potential confounders and empirical concerns, we grant that some may remain. For example, there can be a potential issue of self-selection associated with vehicle choice and VMT. If there are unobserved factors that are correlated with the choice of PEV type and VMT, it can lead to bias in the coefficient estimates corresponding to the powertrain type and other PEV attributes. Future studies by the researchers will account for the selection bias by jointly modeling vehicle choice and VMT.

3.2.3 Analysis of PEV VMT over time

As with ICEVs, miles traveled by a PEV can depend on the age of the vehicle and other vehicle characteristics, as well as sociodemographic and built environment factors. Moreover, since PEVs are a new vehicle technology and usually the PEV is the newest vehicle in a household fleet, buyers may drive the vehicle more just after the purchase than later, due to the “novelty effect,”. Using the dual odometer readings of the ‘Original PEV’, we investigate the relationship between household sociodemographic and household fleet attributes and VMT over time (Period 1 and Period 2 in Figure 2). We estimate a repeated measure mixed model to investigate the change in VMT of PEVs as a function of households’ socioeconomic characteristics, changes in access to charging infrastructure, commute frequency using the PEV, changes in the attributes of the household fleet, and vehicle age. As mentioned earlier, vehicle age is represented here in terms of total months of ownership of the ‘Original PEV ‘(Period 1 and Period 2).

The OLS and the SUR model for single- and multi-vehicle households provide a cross-sectional analysis of the factors that influence PEV use in a household. These models do not allow us to analyze how PEV VMT may change over time. Further, the OLS and the SUR model treats the households as homogenous entities. A mixed model on the other hand is a panel data model that controls for both fixed and random effects allowing us to investigate the factors influencing change in VMT over a given period while controlling for the heterogeneity in response across households. Like the OLS and SUR model, the mixed model will capture, through fixed effects, the influence of the independent variables on the population average. The random effects will allow us to account for any unobserved factor affecting the change in VMT of a PEV; the random effect parameters represent the variability in VMT across households from the population average. For the repeated measure mixed model, we only consider households that retained the Original PEV in the two rounds of the survey (n=2,604). Though odometer data is available for the households that ceased ownership, it is impossible to determine the characteristics of the households at the time of that decision.

Two separate models are estimated for: (i) households that were single-vehicle households during the first and the repeat survey; and (ii) those that were either multi-vehicle during both surveys or moved from being a single- to a multi-vehicle household.

For a **single-vehicle household**, the mixed model is given by

$$VMT_{ij} = \beta_0 + \beta_1 X_{ij} + \vartheta_{0i} + \vartheta_{1i} Months\ of\ ownership_{ij} + \varepsilon_{ij} \tag{5}$$

For a **multi-vehicle household**, the mixed model is given by

$$VMT_{ij} = \beta_0 + \beta_1 X'_{ij} + \vartheta_{0i} + \vartheta_{1i} Months\ of\ ownership_{ij} + \varepsilon_{ij}, \tag{6}$$

<u>where</u> *i*=1, 2…, n households*; j*=1, 2 time periods;

X= (homeownership, dwelling type, access to Level 2 charging at home, household size, frequency of commute with PEV, type of PEV powertrain (BEV/PHEV), and months of ownership interacted with PEV powertrain type);

X'= (number of vehicles, average fuel efficiency of the household fleet (in MPG or MPGe for plug-in vehicles[8]), have a second PEV, homeownership, dwelling type, ratio of PEV age to the second newest vehicle, access to Level 2 charging at home, household size, frequency of commute with PEV, type of PEV powertrain (BEV/PHEV), and months of ownership interacted with PEV powertrain type).

The β coefficients are associated with the fixed component of the model (fixed effects), while the υ coefficients are associated with the two household-type–specific random effects. In the fixed component of the model, we use frequency of commute instead of commute miles, as the latter is endogenous with annual VMT. The interaction variable (*months of ownership interacted with PEV powertrain type*) is included in the model to explain how, on average, the effect of ownership period can vary by powertrain type due to differences in battery degradation and its effect on the electric range. ϑ_{0i}, the random intercept, represents each household's vertical shift from the overall mean (β_0); and ϑ_{1i}, the random slope coefficient, represents each household's deviation from the average linear rate of change of VMT in response to ownership period. (the average response to ownership period is captured by the β coefficient, corresponding to the interaction of powertrain type with months of ownership). In other words, while the random intercept ϑ_{j0} controls for the idiosyncratic differences across households in terms of miles traveled, the random slope ϑ_{j1} controls for the heterogeneity in the effect of ownership period on VMT across households.

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[8] For BEVs and PHEVs we consider the MPGe.

4 Results

First, we present exploratory analysis of PEV VMT, including PEV use in the household fleet. Then we present the results of the econometric models for multi vehicle households and single vehicle households.

4.1 Exploratory Analysis of PEV Use in a Household Fleet

Before we model PEV usage at the household-level and the change in VMT over time, we examine the distribution of VMT of BEVs and PHEVs for single- and multi-vehicle households in the sample. **Figure 3** and **Figure 4** show the distribution of VMT of the Original PEV for single- and multi-vehicle households surveyed in the 2019 repeat survey for the total period of PEV ownership (Period 1 and Period 2 combined).

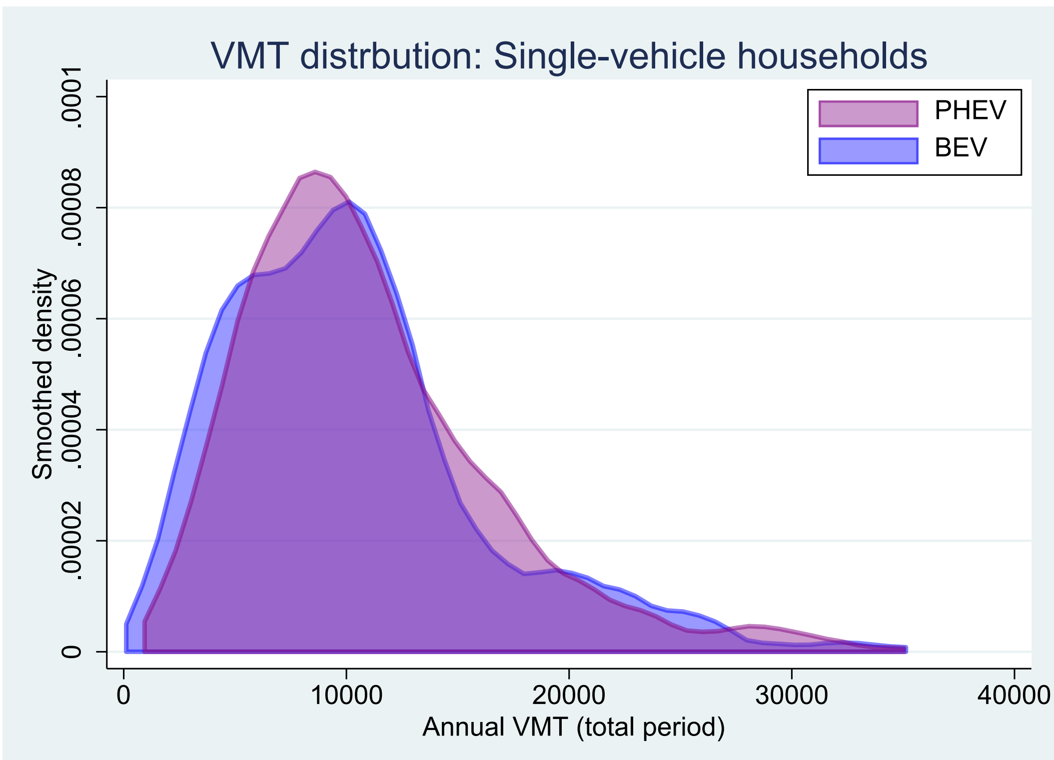


Figure 3: Distribution of PEV VMT from date of purchase/lease to date of "repeat survey" for single-vehicle BEV- and PHEV-owning households

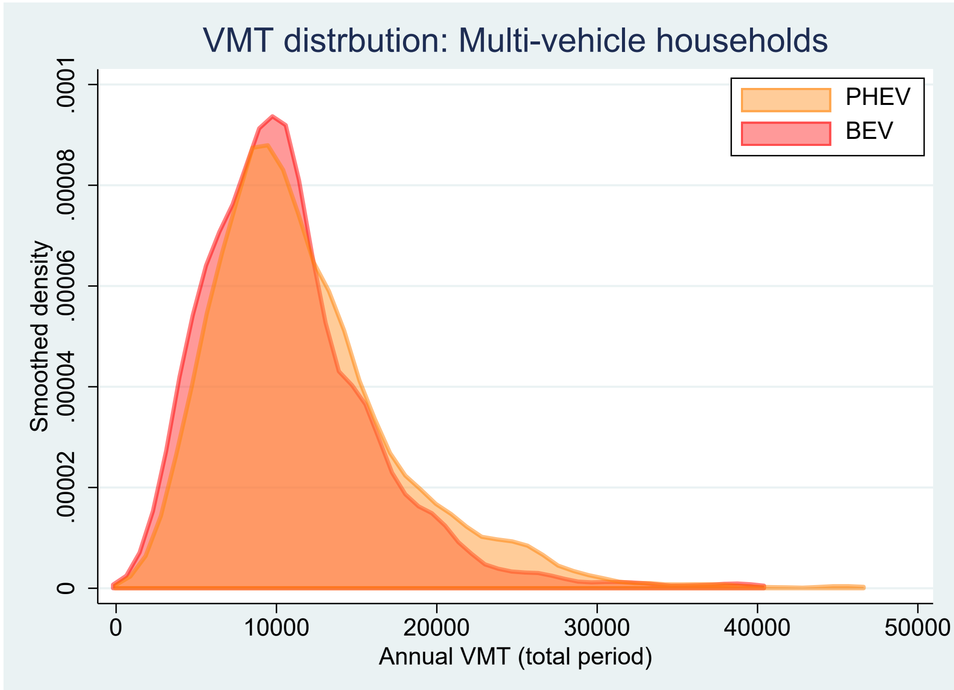


Figure 4: Distribution of PEV VMT from date of purchase/lease to date of "repeat survey" for multi-vehicle BEV- and PHEV-owning households.

We observe that the VMT distribution for single-vehicle households is left-truncated with a long tail of drivers who drive a substantial amount. A two-tailed t-test to check for differences in average VMT between BEV and PHEV households showed that they were not significantly different *(mean=11,607.5 in period 1; mean=10,923.7 in period 2*) among single-vehicle households. Considering the non-normal distribution of VMT, we also use the Wilcoxon rank-sum test to evaluate whether the differences between BEV mileage and PHEV mileage are significantly different. The results indicate that the distributions are not significantly different at a 0.05 significance level. One may expect that due to no range constraints, a single-vehicle household with a PHEV would have a higher VMT than a single-vehicle household with a BEV. However, in our sample, 61% of the single-vehicle households had long-range BEVs (e.g., Chevrolet Bolt or Tesla BEVs). This could be a potential reason for the average VMT of single-vehicle BEV households to be similar to single-vehicle PHEV households. In the case of multi-vehicle households (**Figure 4**), the difference in average and median VMT of BEVs and PHEVs is statistically significant. Results from the t-tests and Wilcoxon sign-ranked test verifying whether the difference in average annual VMT is statistically significant are given below in **Table 4**. In multi-vehicle households, PHEVs are driven more miles per year than BEVs.

Table 4: Difference in VMT between BEVs and PHEVs in single- and multi-vehicle households. In both types of households PHEVs travel significantly more miles than BEVs, though in single-vehicle households the difference is smaller.

Single-vehicle households				
Comparison of Mean (t-test): Diff=mean (BEV) – mean (PHEV) (H_0: diff=0)				
	Mean	**H_a: diff < 0**	**H_a: diff = 0**	**H_a: diff > 0**
BEV (n=225)	10290.02	Prob. (T < t) = 0.1087	Prob. ($\lvert T\rvert$ > $\lvert t\rvert$) = 0.2174	Prob. (T > t) = 0.8913
PHEV (n=288)	10913.45			
Wilcoxon Rank sum Test (H_0: Medians of the two samples are equal)				
P{Annual VMT(BEV) > Annual VMT(PHEV)} = 0.463				
z = -1.445			Prob > $\lvert z\rvert$ = 0.1484	
Multi-vehicle households				
Comparison of Mean (t-test): Diff=mean (BEV) – mean (PHEV) (H_0: diff=0)				
	Mean	**H_a: diff < 0**	**H_a: diff = 0**	**H_a: diff > 0**
BEV (n=2,148)	10703.9	Prob. (T < t) = 0.0000	Prob. (T < t) = 0.0000	Prob. (T < t) = 0.0000
PHEV (n=1,464)	11796.12			
Wilcoxon Rank sum Test (H_0: Medians of the two samples are equal)				
P{Annual VMT(BEV) > Annual VMT(PHEV)} = 0.448				
z = -5.280			Prob > $\lvert z\rvert$ = 0.0000	

Note: The VMT distribution of BEVs and PHEVs for the total period is considered here (Period 1 and Period 2)

H_0 indicates the null hypothesis, and H_a, the alternative hypothesis: i.e, The difference between a household having a PHEV vs. a BEV does not (H_0) or does (H_a) explain the difference in the number of miles a PEV is driven.The PEV VMT in multi-vehicle households, unlike in single-vehicle households, is just a portion of the total household VMT. In a household fleet consisting of both gasoline vehicles and PEVs, a higher share of PEV VMT can lead to greater substitution of gasoline miles with PEV miles. For BEV households, all of these PEV VMT will be electric, in PHEV household some of these PEV VMT will be driven electrically and others with the internal combustion engine. In **Figure 5**, the average share of PHEV VMT in total household VMT is higher than the average share of BEV VMT for both periods (Period 1 and Period 2). The potential for range anxiety or actual range constraints, especially in shorter range BEV, could be a reason for the lower share in the household VMT for BEVs compared to PHEVs. Given the flexibility of the PHEV powertrain, households may consider PHEVs to be more suitable for longer trips than BEVs. Results of the t-tests of the comparisons of the share of annual VMT by BEV or PHEV are given in **Table 5**.

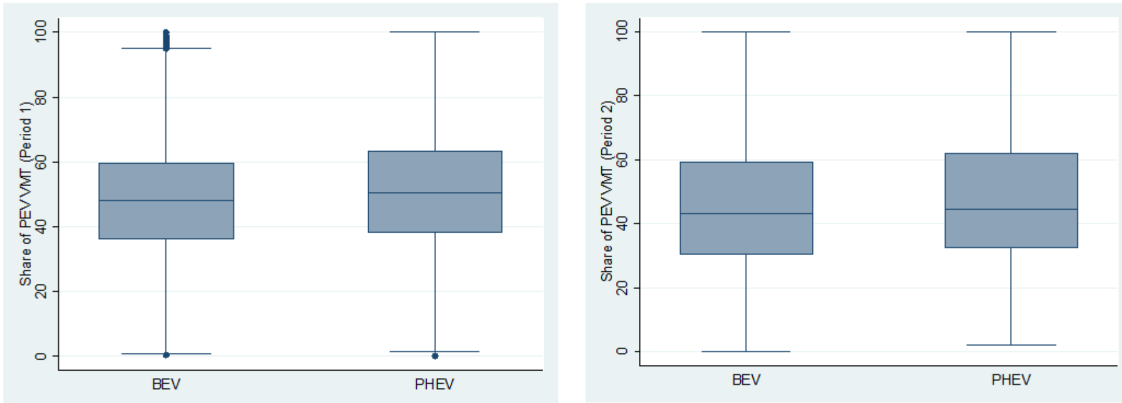


Figure 5: Share of household VMT traveled by the BEV or PHEV in multi-vehicle households in period 1 (left) and period 2 (right). The boxplot shows the median value, 25th percentile (box borders), and 75th percentile (whiskers) of the share of PEV VMT by type of powertrain. The length of each of the boxes represent the interquartile range of the share of VMT completed with a BEV or a PHEV in a multi-vehicle household.

Table 5: t-test results for difference in average share (percentage) of PEV VMT in BEV and PHEV households. In periods 1 and 2, PHEVs travel a larger share of household VMT than BEVs do—a difference that is small but statistically significant.

Comparison of Mean (t-test): Diff=mean (BEV) – mean (PHEV) (H_0: diff=0)

Period 1	**Mean**	**H_a: diff < 0**	**H_a: diff = 0**	**H_a: diff > 0**
BEV (n=2,148) PHEV (n=1,464)	48.51% 51.06%	**Prob. (T < t) = 0.0000**	**Prob. (|T| > |t|) = 0.0000**	**Prob. (T > t) = 1.0000**
Period 2				
BEV (n=2,148) PHEV (n=1,464)	48.92% 50.93%	**Prob. (T < t) = 0.0070**	**Prob. (|T| > |t|) = 0.0140**	**Prob. (T > t) = 0.9930**

H_0 indicates the null hypothesis, and H_a, the alternative hypothesis: i.e, The difference between a household having a PHEV vs. a BEV does not (H_0) or does (H_a) explain the difference in a PEV's share of household VMT.

4.2 Explaining the Relationship between VMT and its Determinants

We now focus on the results from the econometric models examining the relationship between PEV VMT and its determining factors for multi- and single-vehicle households.

4.2.1 Multi-vehicle Households

For multi-vehicle households, the results of the SUR model are shown in **Table 6.** The error components of the two equations in the SUR model are correlated (*correlation= -0.232*). The Breusch Pagan test of independence suggests that we can reject the null hypothesis that the two equations are independent.

Economic Factor: We observe that consumer response to electricity rate at home is elastic. Since both the dependent variable (share of PEV VMT) and the residential electricity rate are logged variables, we can interpret the corresponding coefficient as an elasticity estimate. A one--percent increase in electricity rate ($/kWh) is related to a 2.23 percent lower share of PEV VMT. However, this relationship should be interpreted keeping in mind that the model does not account for the cost of charging (dollar value) at the workplace or public locations. Sensitivity to residential electricity rates can be high if households have access to free workplace charging or discounted public charging. The high elasticity of share of PEV miles to the electricity rate may also be a result of the flexibility households have to use other vehicles in their fleet when the cost of charging is high.

PEV Attributes and Access to Charging Infrastructure: For multi-vehicle households, PEVs with longer electric range have a higher share of household VMT. The results of the SUR model also indicate that access to a Level 2 charger at home has a strong positive effect on the share of PEV VMT. However, access to paid public chargers does not play a significant role in determining the share of PEV in total household VMT. Finally, the results suggest that compared to a PHEV, a BEV has a lower share in the total household VMT, potentially due to range limitations.

Household Sociodemographic and Fleet Characteristics: Characteristics of the household fleet are important for multi-vehicle households in determining the total household VMT and share of PEV VMT. The results of the SUR model suggest that an increase in the average cost of operation of non-PEV vehicles in the fleet reduces total household VMT (see in **Table 6** the variable "Log Cost of operation (non-PEVs)"). But the response is inelastic (-0.06) and not significant at the 1 or 5 percent level of significance (but it is significant at the 10 percent level implying somewhat significant). Having multiple PEVs in a household also does not have a significant effect on total household VMT. Households with at least one van in the fleet have a significantly lower total VMT than other households, while the other vehicle types do not have such a significant effect.

With all other independent variables constant, when the household has multiple PEVs in its fleet (at least one more other than the Original PEV), the share of Original PEV VMT in total VMT decreases by 6 percent. On the other hand, with all else constant, when the cost of driving the non-PEVs in the fleet increases (in average cost per mile), the share of Original PEV VMT in total VMT increases. Households that have an SUV or van in their fleet, compared to those that do not, have a lower share of PEV VMT in the total household VMT. This is perhaps because these households use their van or SUV out of need for a larger vehicle on some journeys, notably long-distance trips. Finally, with all else constant, as the total number of vehicles in the household fleet increases, the total household VMT increases and the share of PEV VMT decreases. Households with larger fleets may not engage in vehicle sharing and are probably less dependent on the PEV for longer trips.

Psychological Factors: Considering the effect of lifestyle preferences, liking suburban living and engaging in outdoor sports or activities have a significant, positive effect on household VMT. Also, pro-technology attitudes and perceived need for a vehicle have a positive influence on total annual VMT by a multi-vehicle household. Lifestyle factors, such as having a stressful commute with congestion and the perceived ability to utilize time spent in congestion, also have a positive effect on VMT. A potential explanation could be that these households usually have a long commute (which they find stressful) leading to higher VMT. In terms of perception towards the PEV technology, we do not observe a significant relationship between attitudes towards PEVs and share of PEV VMT in household VMT.

Built Environment: For multi-vehicle households, living in areas with high population density (i.e. urban areas) or with a higher walkability index has a negative effect on total household VMT. Neighborhood type (urban/suburban) does not have a significant effect on the share of PEV VMT.

Other Determinants of VMT: Among multi-vehicle households, household size positively correlate with total household VMT. The results also suggest that if the PEV is shared by multiple drivers in the household, then the share of PEV VMT is higher. In terms of PEV use patterns, if the PEV is frequently used to commute to work, its share in total household VMT is high. Lastly, the proportion of summer months has a positive effect on the share of VMT and, compared to a leased PEV, those that are purchased have a higher share of VMT, mainly due to the absence of mileage limitations in the latter scenario.

Table 6: Seemingly unrelated regression (SUR) results, modelling independent variables that potentially relate to the share of PEV VMT in total household VMT for multi-vehicle households (n=2,805).

Equation 1				Equation 2			
Log Total Household VMT	**Coef.**	**Signif-icance**	**Std. Err.**	**Share of PEV**	**Coef.**	**Signif-icance**	**Std. Err.**
No. of household vehicles	0.234	***	0.013	Electric Range	0.021	***	0.006
Household size	0.078	***	0.008	Log Electricity Rate Paid	-2.231	***	0.769
Income Category (Base; Less than $100,000)				Shared HHS Vehicle (No=1)	-2.791	***	0.965
$100K-$199K	0.049		0.027	BEV (Yes=1)	-5.201	***	0.989
$200K-$299K	0.044		0.030	Purchased (Base: Leased)	3.523	***	0.667
More than $300K	0.000		0.033	PEV age/Age of second newest vehicle	-0.037		0.027
Decline to state	-0.046		0.034	Proportion of summer months	3.849	**	1.943
Liking for Suburban Living	0.033	***	0.009	Freq. of commute with PEV	0.532	***	0.134
Stressful commute with congestion	0.029	***	0.008	Number of Vehicles	-8.239	***	0.416
Liking for Outdoor life	0.018	**	0.008	Home Own (Yes=1)	-0.814		1.156
Pro-technology	0.020	**	0.008	Detached home (Yes=1)	-0.094		1.070
Not Active Lifestyle	0.015		0.008	Level 2 Charger @ Home (Yes=1)	2.290	***	0.693
Liking for store shopping	0.015		0.008	Paid public charging (Yes=1)	0.412		0.610
Have need for a vehicle	0.016		0.008	Respondent gender (Male=1)	1.204		0.722
Time utilization in Congestion	0.023	***	0.008	**Respondent age (Base: 15-30 years)**			
Population density	-0.003	**	0.001	30-60 yrs	0.455		1.999
National Walkability Index	-0.010	***	0.002	60 yrs and older	-1.212		2.093
Place type (Base: Urban)				Safety and environment conscious	0.018		0.302
Suburban	0.026		0.033	Range and charging convenience conscious	0.105		0.357
Rural/Non-urban	0.019		0.050	More than one PEV (Yes=1)	-5.910	***	1.219
More than one PEV (Yes=1)	0.021		0.033	Log Cost of operation (non-PEVs)	7.020	***	1.130

Equation 1				Equation 2			
Log Total Household VMT	**Coef.**	**Signif-icance**	**Std. Err.**	**Share of PEV**	**Coef.**	**Signif-icance**	**Std. Err.**
Log Cost of operation (non-PEVs)	-0.061		0.032	**Place type (Base: Urban)**			
Average Age of other Vehicles	-0.004		0.003	Suburban	0.315		1.045
Square of Avg. Age of other Vehicles	0.000		0.000	Rural/Non-urban	1.780		1.464
Has at least one Van (Yes=1)	-0.069	**	0.029	Has at least one Van (Yes=1)	-4.318	***	1.059
Has at least one SUV (Yes=1)	-0.001		0.020	Has at least one SUV (Yes=1)	-4.108	***	0.713
Has at least one Pickup (Yes=1)	0.005		0.028	Has at least one Pickup (Yes=1)	0.770		1.046
Constant	9.218	***	0.095	Constant	91.289	***	4.389

*** denotes significant at the 1% level, ** denotes significant at the 5% level.

4.2.2 Single-vehicle Households

The results of the OLS regression and quantile regression (QR) models for single-vehicle households are given in

Table 7. In the QR model, the coefficients for each quantile measure the effect of the explanatory variables on the response of the households belonging to the corresponding quantile in the observed VMT distribution. Note the use of OLS and QR, rather than SUR, for single-vehicles households.

Economic Factors: As in the case of multi-vehicle households, electricity rate at home will capture a PEV driver's response to changes in operating cost of the vehicle in terms of miles driven. The OLS regression model as well as the QR model shows that with all else constant, on average, the consumer response to residential electricity rate is inelastic. Moreover, contrary to the usual hypothesis about consumer response to the cost of driving, we observe a positive coefficient indicating a small increase in VMT in response to a higher residential electricity rate ($/kWh). However, we do not find the effect to be significant in the OLS or the five quantiles of the QR model. One potential reason for the lack of a significant relationship (i.e., elasticity) between VMT and electricity price is that these single-vehicle houses have less flexibility in adjusting their travel choices than do multi-vehicle households.[9]

PEV Attributes and Access to Charging Infrastructure: The effect of electric range is not significantly correlated to the VMT of the PEV. However, we observe that households with non-Tesla BEVs have lower VMT compared to households with a Tesla. This does not necessarily imply a causal relationship—i.e., that owning a Tesla rather than another make BEV leads to more VMT. Such a conclusion is not supported because even though the model has a rich set of control variables, some unobserved factor(s) that we did not control for may influence the choice of the household PEV and VMT. Households with higher travel needs or preference for technology features such as autopilot may choose long-range BEVs like Tesla and in turn have higher VMT; see Hardman (*38*) for analysis of the impact of vehicle automation (including Tesla's Autopilot) on VMT. In terms of the effect of access to charging opportunities, single-vehicle households with a Level 2 charger at home have a higher VMT on average than those with no charging or a Level 1 charger at home. This result is consistent with the findings of past studies on the relationship between the driving behavior of PEV owners and access to home-charging facilities (*30*, *37*). Considering the QR model, access to a Level 2 charger at home has a significant effect on households in the higher (50th and 75th) quantiles of the VMT distribution. Having level 2 charging at home can permit more electric miles due to faster charging times. Once again, the result needs to be interpreted with caution due to potential endogeneity issues. Households may opt to install a level 2 charging because they desire to use their BEV more (an unobserved factor).

Access to paid public charging infrastructure does not have a significant relationship with VMT in single-vehicle households. Unlike the OLS regression model, the results of the QR model suggests that access to public charging infrastructure (even when paid) has a significant positive effect on the VMT of households in the higher quantiles (75th and 90th) of the VMT distribution. This may mean that public charging only has an impact on VMT in households that drive more than the average annual VMT, or that households that need to travel farther are forced to use public charging to meet their higher VMT needs.

Household Sociodemographic and Vehicle Characteristics: For one vehicle households, none of the sociodemographic characteristics have a statistically significant effect on total household VMT. In terms of vehicle characteristics, having a BEV, compared to a PHEV, is negatively related to VMT. According to

[9] A separate model was estimated with PEV commuters accounting for the effect of availability and the cost of workplace charging. Results of the OLS regression model is given in Appendix B of the report. The effect of free workplace charging on VMT is not significant. There is a possibility of self-selection with PEV drivers who have access to free workplace charging such that they are more likely to use a PEV for longer commutes than those without free workplace charging.

the OLS model results, miles driven in a BEV are on average 23% less than a PHEV in single-vehicle households. In the QR model, the effect of powertrain on annual VMT is significant for the median and the 75th quintile of VMT distribution, suggesting that the range of a BEV can be a constraint only for households with higher travel needs.

Psychological Factors: The results of the OLS regression suggest that on average, lifestyle preferences such as having a liking for suburban living and outdoor activities correlate positively with annual VMT. However, as the QR model results show, the magnitude of the effect of a "liking for suburban living" is higher for households in the higher quantiles of the VMT distribution than those closer to the mean. Having a "liking for outdoor activities" has a significant effect on VMT only for households in the 25th quintile. Moreover, for households in the 90th quantile, a positive perception of PEVs in terms of environmental consequences and safety compared to gasoline cars correlates with a lower VMT.

Built Environment and Other Determinants of VMT: The relationship between any of the built environment factors and VMT is not significant for the single-vehicle households, except for living in a suburban neighborhood. For households in the 25th quintile of the VMT distribution, living in a suburban neighborhood compared to an urban area is associated with higher VMT. Considering the effect of the other control variables in the model, the QR results show that the purchase/lease decision tends to affect households only in the higher VMT quantiles (75th and 90th). Since vehicle lease contracts have a mileage cap, this could constrain households with high travel needs. In terms of variables related to driving behavior, the effect of proportion of summer months is positive and significant, suggesting that households may use their PEVs for longer trips during summer months. Households who use their PEV more frequently for commuting have higher VMT, with a stronger effect for households in the 75th quantile than the 25th or the average. When the single PEV in the household is shared by multiple drivers the number of annual miles traveled is higher than when it is not shared. Finally, the coefficient on the variable controlling for the gender of the respondent suggests that male respondents report a higher number of miles traveled than women do.

Table 7: Ordinary least squares and quantile regression models for single-vehicle households where PEV annual VMT is the dependent variable (n=459).

	OLS	Quantile Regression				
Log HHS VMT	**Coefficient**	**q10**	**q25**	**q50**	**q75**	**q90**
Log electricity rate paid	0.017	0.009	0.000	0.001	0.003	0.108
Electric range	0.000	0.001	0.001	0.000	-0.001	-0.001
Shared or not (Not=1)	0.190 ***	0.142	0.155	0.204	0.148	0.153
BEV or not (Base: BEV)	-0.234 **	-0.376	-0.312 ***	-0.194	-0.207	0.126
Car is not Tesla (Base: Tesla)	-0.276 **	-0.278	-0.322	-0.199	-0.372 **	-0.281
Purchase/Lease (Purchase=1)	0.064	-0.098	0.000	0.148 **	0.131	0.152
Proportion of summer months	0.242	0.411	0.489 **	0.158	0.084	0.048
Freq. commute use	0.028 **		0.039 **	0.033 **	0.048 **	0.024
Number of months owned (Base: less than 5 months)						
5-10 months	-0.081	0.168	-0.075	-0.015	-0.195	-0.142
10-16 months	-0.095	0.026	-0.040	-0.063	-0.120	-0.030
16-25 months	-0.122	-0.048	-0.048	0.014	-0.182	-0.150
> 25 months	-0.078	-0.039	0.055	0.009	-0.260	-0.121
Household size	-0.009	-0.084	-0.048	-0.002	0.050	-0.012
Income Categories (Base: Less than $100,000)						
$100K-$199K	0.034	0.083	0.023	-0.067	-0.003	-0.056
$200K-$299K	-0.008	-0.084	0.008	-0.080	-0.089	-0.184

	OLS	Quantile Regression				
Log HHS VMT	**Coefficient**	**q10**	**q25**	**q50**	**q75**	**q90**
More than $300K	0.055	0.294	0.097	0.038	-0.022	-0.085
Decline to state	0.014	0.124	-0.066	0.025	-0.018	-0.080
Homeownership (Own=1)	-0.104	-0.098	-0.137	-0.093	-0.062	-0.005
Detached home (Yes=1)	0.031	0.194	0.102	-0.022	-0.073	-0.101
Level 2 Charger at home (Yes=1)	0.158 **	0.148	0.137	0.268 **	0.220	0.001
Access to paid public charging (Yes=1)	0.080	-0.003	0.043	0.162	0.175 **	0.174 **
Gender (Male=1)	0.122 **	0.147	0.172	0.165	0.086	0.053
Age Categories (Base: 15-30 years)						
30-60 yrs	-0.015	-0.103	-0.039	0.113	-0.193	-0.034
60 yrs and older	-0.185	-0.317	-0.220	-0.088	-0.260	-0.145
Safety and environment conscious	-0.027	0.106	0.035	-0.064	-0.073	-0.117 **
Range and charging convenience conscious	0.023	-0.020	0.005	0.042	0.017	0.084
Liking for Suburban Living	0.053 **	0.011	0.022	0.033	0.070 **	0.113 ***
Stressful commute with congestion	-0.004	0.057	-0.007	-0.020	-0.013	-0.022
Liking for Outdoor life	0.046	0.051	0.065	0.037	0.001	0.029
Pro-technology	0.025	0.003	0.035	0.033	-0.014	-0.037
Not Active Lifestyle	-0.014	0.028	-0.028	-0.023	0.001	-0.035
Liking for store shopping	0.027	0.019	-0.008	0.035	0.055	0.029
Have need for a vehicle	-0.037	-0.015	-0.027	-0.030	-0.042	-0.048

	OLS	Quantile Regression				
Log HHS VMT	**Coefficient**	**q10**	**q25**	**q50**	**q75**	**q90**
Time utilization in Congestion	0.025	0.011	0.008	0.052	0.009	0.014
Population density	0.003	0.090	0.051	-0.016	-0.020	-0.045
National Walkability Index	-0.013	-0.020	-0.011	-0.003	0.000	0.000
Place type (Base: Urban)						
Suburban	0.083	0.192	0.172 **	0.161	0.142	0.109
Rural/Non-urban	0.153	0.656	0.434	0.256	0.228	0.069
Constant/Intercept	9.245 ***	8.397 ***	8.741 ***	8.841 ***	9.751 ***	9.788 ***

*** denotes significant at the 1% level, ** denotes significant at the 5% level.

4.2.3 Analysis of PEV use over time in Single- and Multi-vehicle Households

As illustrated in the econometric models above for multi- and single-vehicle households, VMT of PEVs is affected by household fleet characteristics, lifestyle preferences, access to and cost of home charging, and PEV characteristics like type of powertrain (BEV/PHEV) or electric range for multi-vehicle households. Vehicle age represented here by the number of months of ownership since purchased/leased new is another vehicle characteristic that we hypothesize can have an effect on VMT (based on the literature (*18*) and data for gasoline vehicles).[10] However, number of months of ownership of the 'Original PEV' in Period 1 on average did not have a statistically significant effect on VMT for single-vehicle households. A potential reason could be that the average PEV ownership time was only 1 year 1 month in Period 1. By the time of submission of the repeat survey (Total period as shown in **Figure 2**), the average ownership period of the 'Original PEV' was 4 years, 4 months (25^{th} percentile: 2 years, 4 months; and 75^{th} percentile: 4 years, 3 months). Therefore, to have a better understanding of the effect of vehicle age/months of ownership on PEV use in a household fleet, we analyze how PEV VMT in single- and multi-vehicle households may change in response to an increase in months of ownership (Total period as shown in **Figure 2**) with a mixed effect model described earlier. The results of the mixed effect model are given in **Table 8**.

[10] Vehicle miles traveled by age and vehicle segment: https://nhts.ornl.gov/tables09/fatcat/2009/best_VEHAGE_VEHTYPE.html.

Table 8: Result of repeated measures model for single- and multi-vehicle households. The dependent variable for both household types is the VMT estimated at two time points (i.e., Period 1 and Period 2).

	Multi-vehicle Households			Single-vehicle Households		
Dependent Variable: Log AnnualVMT	**Coefficient**		**Std. Err.**	**Coefficient**		**Std. Err.**
Fixed Effect Parameters						
Home Own (Yes=1)	-0.045		0.034	-0.094		0.066
Detached Home (Yes=1)	0.026		0.031	0.015		0.059
Level 2 @ Home (Yes=1)	0.045	***	0.016	0.098	*	0.059
Household size	0.059	***	0.008	-0.006		0.030
Freq. of commute	0.015	***	0.003	0.004		0.006
PHEV (Base=BEV)	0.067	**	0.031	0.090		0.077
BEV × Mnths of ownership	-0.004	***	0.001	-0.005	***	0.002
PHEV × Mnths of ownership	-0.004	***	0.001	-0.005	***	0.002
Income Category (Base; Less than $100,000)						
$100K-$199K	0.063	**	0.027	0.057		0.052
$200K-$299K	0.049		0.031	-0.136		0.095
More than $300K	0.061	*	0.035	-0.053		0.143
Decline to state	0.007		0.033	0.067		0.066
Number of HHS Vehicles	-0.006		0.010			
Avg. MPG HHS Fleet	-0.001	*	0.000			
PEV Age/ Age of Second Newest Veh	0.001		0.001			
Have a Second PEV (Y=1)	-0.001		0.030			
Constant/Intercept (Population Average)	9.071	***	0.053	9.134		0.088
Random Effect Parameters						
Estimated variance (Individual-level)	0.521		0.015	0.449		0.026
Estimated variance (Powertrain × Months of ownership)	0.010		0.001	0.007		0.002
Correlation (constant, Mnths of ownership)	-0.557		0.037			
Log-likelihood	-3228.11			-407.01		
No. of observations	4484			586		

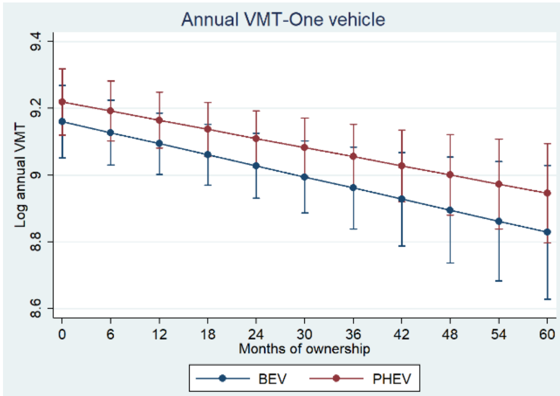
*** denotes significant at the 1% level, ** denotes significant at the 5% level, * denotes significance at the 10% level.

The results from the fixed portion of the model suggest that for single-vehicle households, on average PEV VMT increases when households have access to a Level 2 charger at home. None of the other household or socioeconomic characteristics have a significant effect on VMT. On average, the type of powertrain (BEV or PHEV) does not have a statistically significant effect on VMT over time, but the interaction between type of powertrain and ownership period is significant, with months of ownership having a similar negative effect on both BEV- and PHEV-VMT. Similarity in the effect of vehicle age(measured as months of ownership) is confirmed by the t-test results that suggest the average effect of months of PEV ownership on VMT does not differ by the type of powertrain (H_0: *BEV#monthsownedperiod − PHEV#monthsownedperiod = 0; chi2(1) =0.11; Prob > chi2 =0.7387*). Considering results from the random part of the model, both the random intercept and the random slope on *Months of ownership* exhibit significant variation, indicating substantial household-to-household differences both in the mean VMT and in how vehicle age or months of ownership affects VMT.

For multi-vehicle households, the fixed portion of the model suggests that on average, VMT increases with larger household size, higher frequency of commute, and access to a Level 2 charger at home. The effect of the type of powertrain on VMT is significant for multi-vehicle households, with PHEVs being driven on average more annual miles than BEVs. This could be a result of a multi-vehicle households substituting their BEV with a gasoline vehicle for some journeys. Since PHEVs do not have the range limitations of BEVs they may be used for more journeys regardless of length. In multi-vehicle households, as in single-vehicle households, although months of ownership have a negative effect on VMT (older vehicles traveling fewer miles per year), the effect of powertrain on VMT over time is on average not different between BEVs and PHEVs. Also, both the random intercept and the random slope on *Months of ownership* exhibit significant variation, indicating substantial differences across households in terms of average VMT and in how they respond to vehicle ownership period.

Figure 6 presents the average effect of the period of PEV ownership on VMT for single- and multi-vehicle households.[11] In both cases, single- and multi-vehicle households, PHEVs have a higher annual VMT than BEVs. Electric range constraints preventing the use of a BEV for long trips or range anxiety can be potential reasons for this observation. Moreover, the downward slope of the line suggests that both BEV and PHEV use reduces with vehicle age or months of ownership, although the change we observe here is very small. The average period of ownership (Total Period of analysis) among single- and multi-vehicle households is on average 40 months (median, 36 months), i.e., less than 4 years. This relative short period of ownership of the PEVs may explain the small change in VMT observed here. The analysis presented in this report shows how PEV use changes over a relatively short period of time. To investigate how BEVs and PHEVs will be used by households over the lifetime of the vehicle, odometer readings over a longer time horizon are required.

[11] Regarding this relationship: the standard error corresponding to the marginal effect estimates is larger for longer periods of PEV ownership. This is potentially caused by the fact that the number of households with the Original PEV for more than 4 years is considerably smaller than the number with the Original PEV for less than 2 years. (In the full sample, the years of ownership median is 36 months and average is 41 months.)



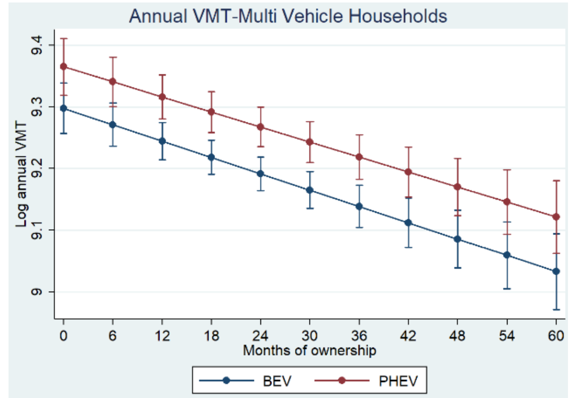


Figure 6: Months of PEV Ownership and VMT of Single- and Multi-vehicle Households.

5 Discussion and Conclusion

The results of this study represent one of the first in depth investigations into VMT of PEVs. We hope the results will help inform future efforts to model systemwide light-duty vehicle emissions, emissions of PEVs, and travel behavior of drivers of PEVs with better assumptions on how PHEVs and BEVs will be used. The results show that, similar to conventional vehicle use, PEV use is correlated to socio-demographic variables, attitudes or lifestyles, and built environment factors (*40*). For PEVs two additional factors have a strong relationship with vehicle use: the range of the vehicle (particularly in multi-vehicle households) and whether drivers have access to level 2 charging at home. These two factors appear to be the major determinants of whether a household can substitute gasoline miles with electric miles.

In a multi-vehicle household, the contribution of a PEV to household VMT increases with the range of the vehicle, this is important for BEVs and shows that longer-range BEVs (>300 miles like the existing Tesla models) may give households greater electric mobility than shorter-range BEVs (<150 miles like the fist-generation BEVs). Since most new and upcoming BEVs are longer-range vehicles, we expect this to mean BEVs will largely be suitable replacements for conventional vehicles in household fleets. Compared to BEVs, PHEVs have slightly higher VMT and a slightly higher share of household VMT. In multi-vehicle households PEV VMT decreases with household electricity price. Lower electricity rates may encourage drivers to use their PEV more often. PEV VMT increases when households have access to higher power (level 2) charging from home, indicating that level 2 home charging increases the potential of PEVs to displace conventional vehicle miles. This finding underscores the importance of home charging, as has been shown in other studies. Those studies indicated that the availability of home charging (compared to public or work-place charging) is the most influential in the decision to purchase a PEV, and that after purchase, home is the most frequently used charging location (*41*). In addition, home charging offers the lowest cost and greatest convenience, and it increases the probability of continuing PEV ownership (*4*).

In single vehicle households electric driving range and home electricity price are not correlated with VMT. This may be because single-vehicle households do not have the flexibility that multi-vehicle households do in substituting one vehicle for another. Having level 2 charging access at home is correlated with VMT in in both single- and multi-vehicle households, again highlighting the importance of level 2 home charging. Living in a suburban neighborhood, and drivers' attitudes (e.g., preferences for outdoor activities) are also positively correlated with VMT in the single-vehicle household models.

Finally, the results of the mixed effect model indicate that PEV VMT trends slightly downward as time of ownership advances. This result comes from data of mostly new vehicles owned over a relatively short period of time. Longer periods of data collection are needed to determine whether this trend continues, flattens out, or reverses with longer ownership periods.

Two recent studies on VMT among PEV owners suggested they are driving their vehicles less than conventional vehicle owners (*1*, *2*). In contrast, we find that PEV owners are driving as much as conventional vehicle owners. This difference in results may be due to the other studies using data mostly from earlier years (pre-2016), a smaller dataset, and a less diverse sample of PEVs (makes, model, and electric range). Considering the driving behavior of existing PEV owners, the current study supports the idea that PEVs can be viable replacements for conventional vehicles, for California households. This would mean that even as PEVs replace gasoline vehicles in the light-duty vehicle fleet, policies are needed to reduce VMT and the associated negative externalities like congestion; the change to PEVs alone may not yield a VMT decrease.

In contrast to the claim that PEVs are being driven less than gasoline and hybrid vehicles, some suggest that the lower operating costs of PEVs will lead to a rebound effect. We find no evidence that the lower running costs of PEVs will cause drivers to travel more, though we cannot rule this out as a possibility. More research is needed to conclusively state the quantitative relationship between PEV operating cost and VMT. One way to explore this would be to track VMT in conventional vehicle owning households and then measure these same households once they transition to PEV ownership. It may be possible to re-survey households in this study's cohort sample of existing PEV owners that still own at least one ICEV and record any changes to their VMT once this ICEV has been replaced with a PEV.

6 References

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7 Appendix A

Here, we discuss the composition of the sample of vehicles in the NHTS, CVS, and the two UC-Davis surveys based on vehicle model year. First-generation BEVs from all automobile manufacturers except Tesla were mostly short-range (less than 150 miles). Owing to technological advancements and to meet consumer demand for longer electric range, auto manufacturers have started offering longer-range BEVs in more recent years. In other words, the model year of a PEV can offer a good representation of the improvements in the electric range of these powertrains.

7.1 2017 National Household Travel Survey - California Add On

The NHTS survey is conducted periodically at the national level. The NHTS data used here were collected between April 19, 2016, and April 25, 2017. Figure 7-Figure 9 give the distribution of the model years of BEVs, PHEVs, and ICEVs in the California Add-on sample, collected by the California Department of Transportation. In all three cases, we consider vehicle models post 2008.

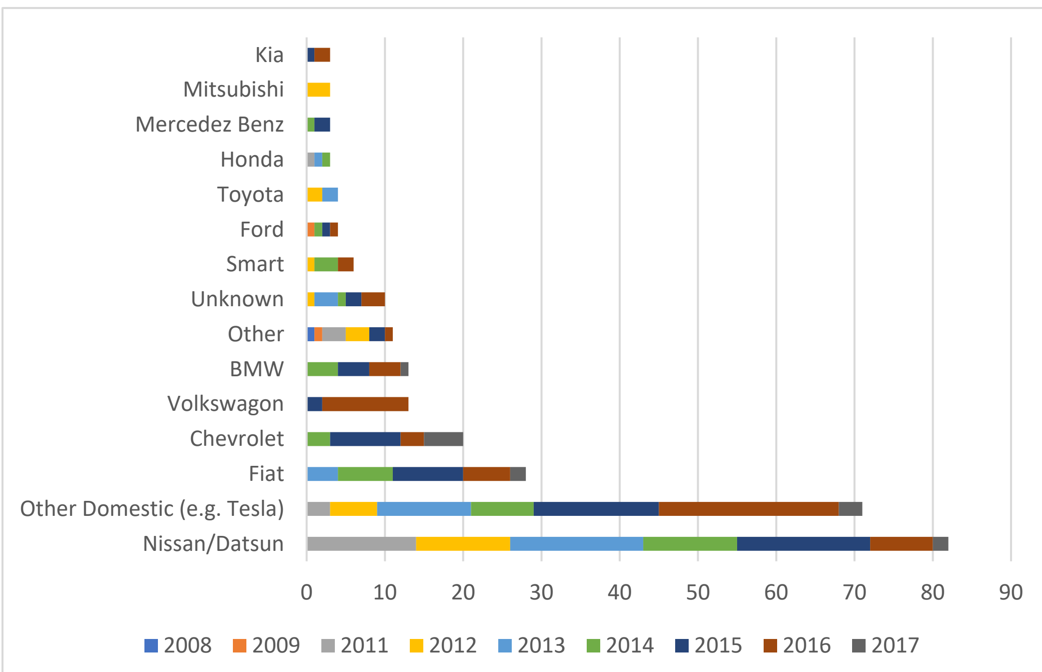

Figure 7: Model Years of BEVs in the NHTS sample (n=274). This graphs shows the number of BEVs of different model years (2008-2017) by vehicle make in the 2017 NHTS Californial Add On sample. In general, the sample has a larger share of short-range (<120 miles) BEVs (e.g., Nissan Leaf pre-2016 or the Fiat 500e). There are long-range BEVs (>200 miles) in the sample like the Teslas, but the rest of the BEV models are primarily short-range.

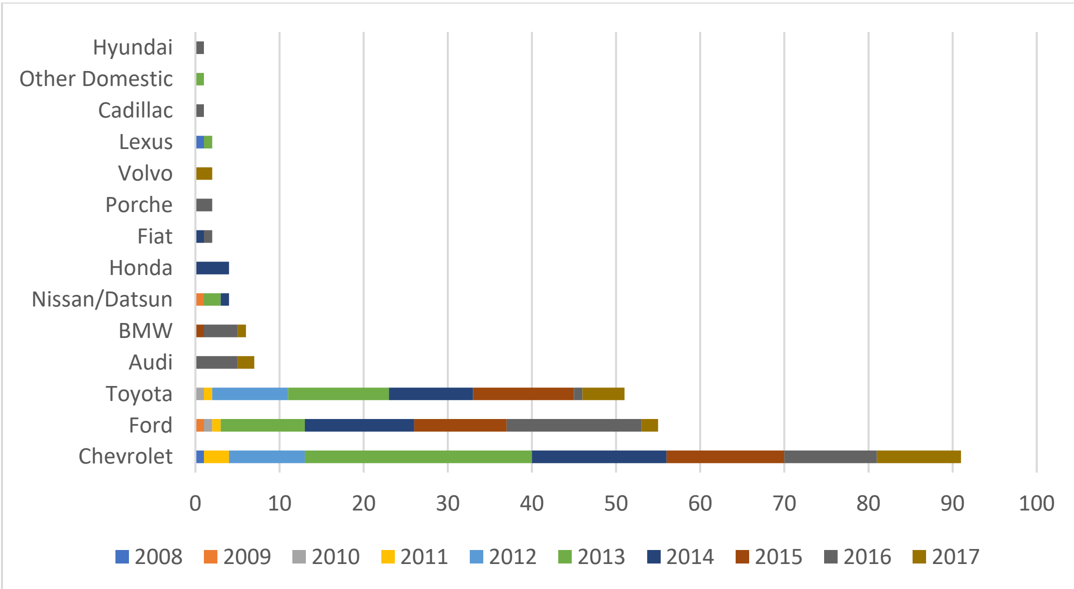

Figure 8: Model Years of PHEVs in the NHTS sample (n=229). This graphs shows the number of PHEVs of different model years (2008-2017) by vehicle make in the 2017 NHTS Californial Add On sample. In general, the sample has a large share of Chevrolet Volt, Toyota Prius Prime (pre-2016 with electric range of 11 miles), and PHEVs by Ford.

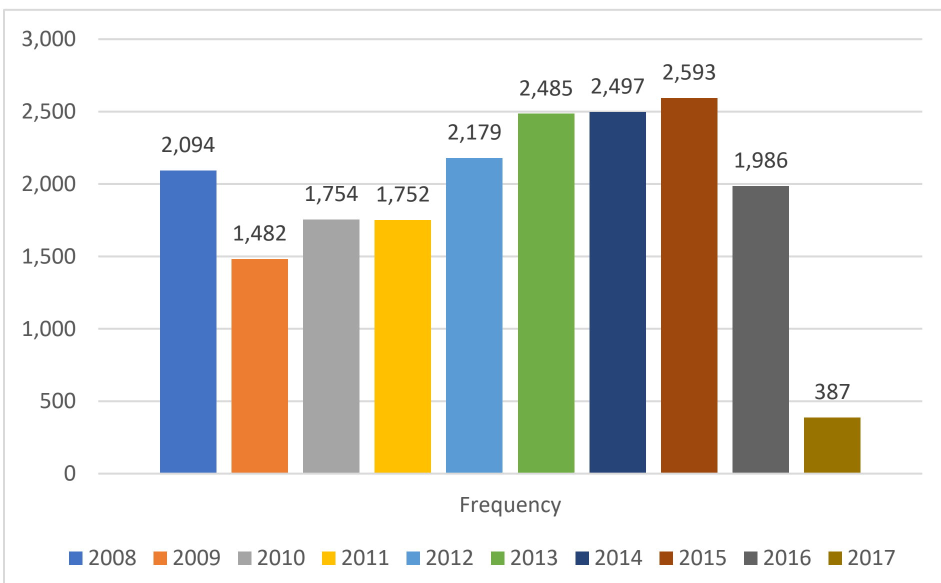

Figure 9: Model Years of ICEVs in the NHTS sample (n=19,209). This graphs shows the number of ICEVs of different model years (2008-2017) in the 2017 NHTS Californial Add On sample. The sample of vehicles in the 2017 NHTS California Add On analyzed here (model years 2008-2017) was dominated by ICEVs, with a considerable share of new vehicles consideing the survey dates (model years 2014-2016). The number of vehicle makes for ICEVs is large, not possible to split the numbers by make.

7.2 2019 California Vehicle Survey- California

The California Vehicle Survey (CVS) is conducted periodically by the California Energy Commission to support travel demand forecast models as vehicle technologies and preferences change over time. Figure 10 -Figure 12 give the distribution of model years of BEVs, PHEVs, and ICEVs in the sample.

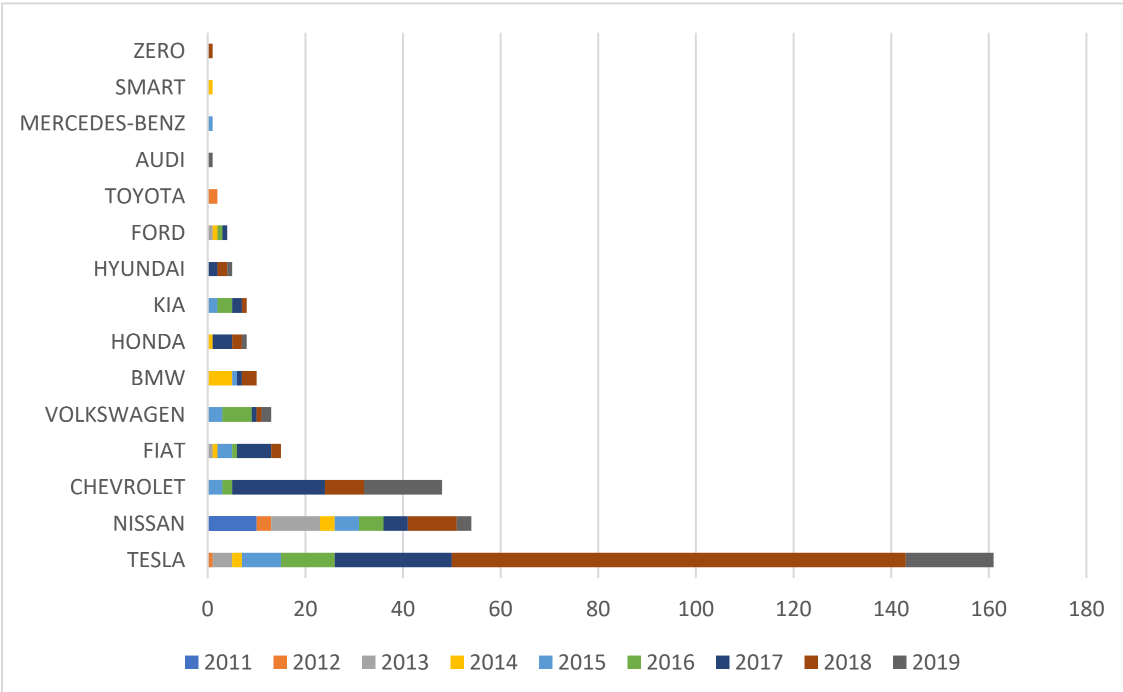

Figure 10: Model years of BEVs in the CVS sample by Make (n=332). This graphs shows the number of BEVs of different model years (2008-2019) by vehicle make in the 2019 California Vehicle Survey sample. Unlike the 2017 NHTS data described earlier, the sample has a larger share of long-range BEVs (>200 miles) like the Teslas and the Chevrolet Bolt.

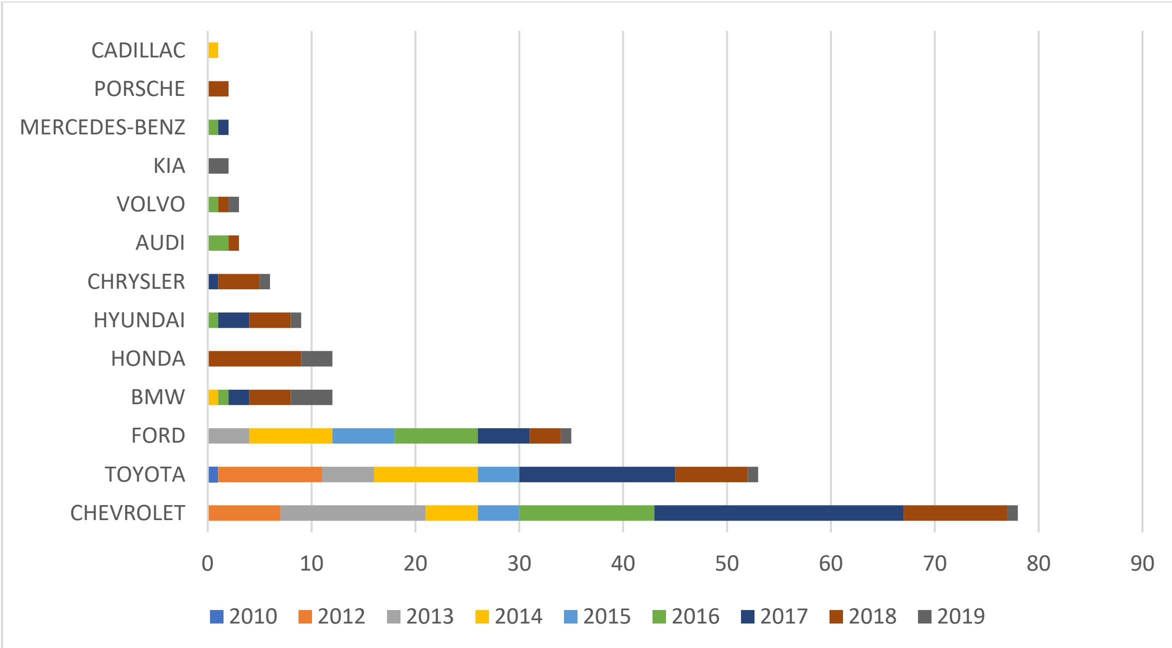

Figure 11: Model years of PHEVs in the CVS sample by Make (n=218). This graphs shows the number of PHEVs of different model years (2008-2019) by vehicle make in the 2019 California Vehicle Survey sample. Similar to the 2017 NHTS data, the sample has a large share of Chevrolet Volt, Toyota Prius Prime, and PHEVs by Ford, but more recent model years (e.g, the Prius Prime with 25 miles of electric range).

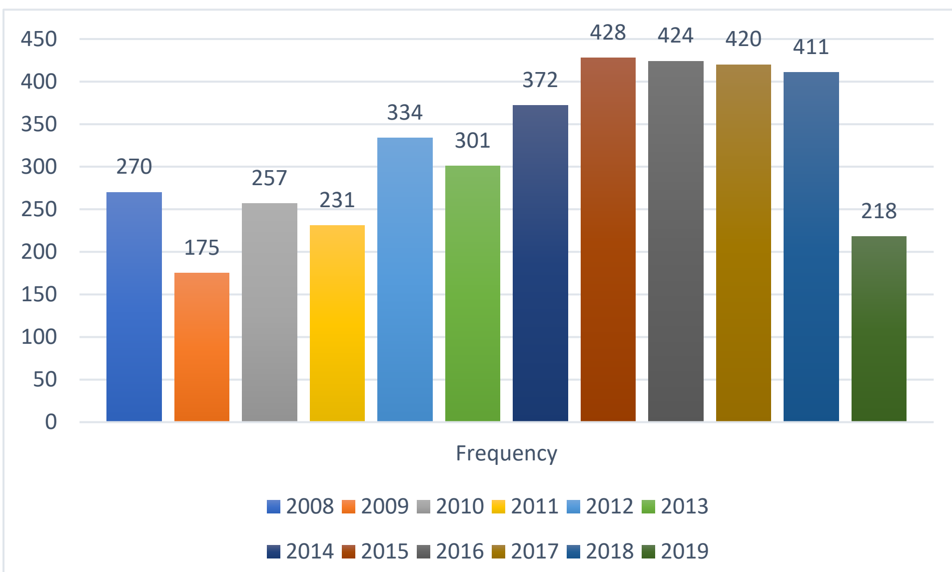

Figure 12:Model years of ICEVs in the CVS sample (n=3,841). This graphs shows the number of ICEVs of different model years (2008-2019) in the 2019 California Vehicle Survey sample. The sample of vehicles analyzed here (model years 2008-2017) was dominated by ICEVs, with a considerable share of new vehicles consideing the survey dates (model years 2015-2018). The number of vehicle makes for ICEVs is large, not possible to split the numbers by make.

7.3 UC Davis eVMT Survey (Phase 1 -Phase 4)

The Plug-in Hybrid and Electric Vehicle (PH&EV) Research Center in UC Davis administers a periodic cohort survey of plug-in electric vehicle owners in California. The sample is recruited from the pool of applicants of the state rebate offered through the Clean Vehicle Rebate Project. The 4 phases of the survey analyzed here were conducted between 2015 and 2019. Figure 13 and Figure 14 give the distribution of model years of BEVs and PHEVs in the sample.

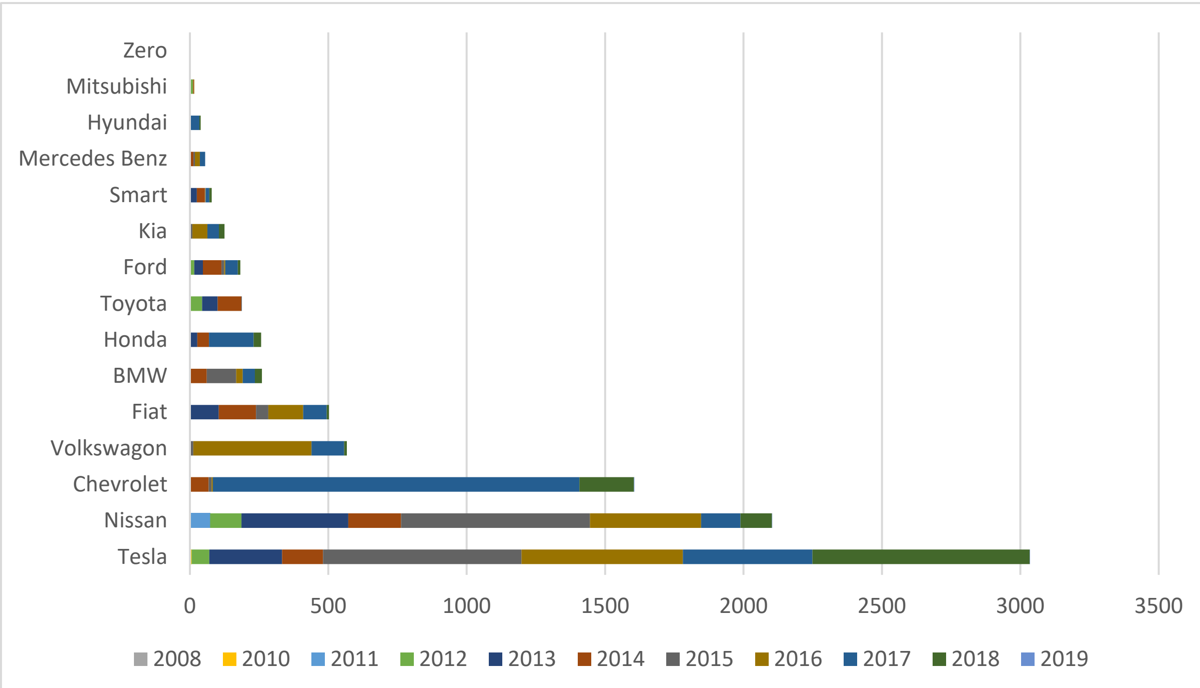

Figure 13: Models years of BEVs in the UC Davis eVMT Survey sample (n= 9,014). This graphs shows the number of BEVs of different model years (2008-2019) by vehicle make in the multi-round UC Davis eVMT survey sample. Unlike the two other datasets described earlier, the sample covers a wider range of BEV models and years, including both short-range (<120 miles) and long-range BEVs (>200 miles) like the Teslas and the Chevrolet Bolt.

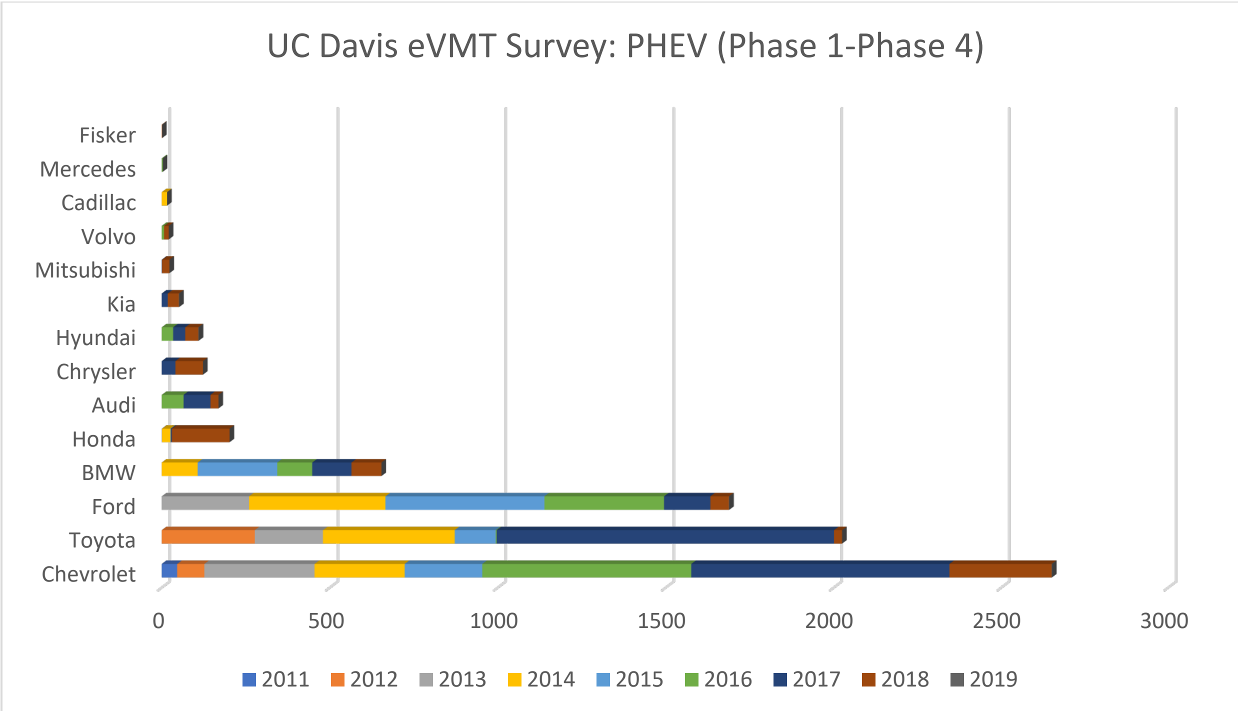

Figure 14: Models years of PHEVs in the UC Davis eVMT Survey sample (n=7,741).). This graphs shows the number of PHEVs of different model years (2008-2019) by vehicle in the multi-round UC Davis eVMT survey sample.

8 Appendix B

Table 9: VMT of the Original PEV in oSingle-Vehicle households where the commuter using the PEV has access to chargers at the workplace (n=341, R^2 =0.1882)

Log Household VMT	**Coef.**	**Std. Err.**	**P>|t|**
Log electricity rate paid	0.017	0.083	0.837
Electric range	0.000	0.001	0.595
Shared or not (No=1)	0.028	0.106	0.793
BEV or not (BEV=1)	-0.147	0.103	0.153
Car is not Tesla (Yes=1)	-0.184	0.134	0.172
Purchase/Lease (Purchase=1)	0.145	0.063	0.022
Free workplace charging	-0.066	0.088	0.452
Household size	-0.002	0.038	0.952
Income Categories (Base: Less than $100,000)			
$100K-$199K	0.014	0.073	0.848
$200K-$299K	-0.034	0.120	0.775
More than $300K	0.099	0.188	0.598
Decline to state	-0.015	0.110	0.891
Homeownership (Own=1)	-0.120	0.078	0.124
Detached home (Yes=1)	0.057	0.073	0.434
Level 2 Charger at home (Yes=1)	0.116	0.075	0.123
Access to free public charging (Yes=1)	0.142	0.061	0.021
Gender (Male=1)	0.126	0.065	0.052
Age Categories (Base: 15-30 years)			
30-60	0.007	0.108	0.951
60 and older	-0.185	0.131	0.159
Safety and environment conscious	-0.062	0.032	0.055
Range and charging convenience conscious	0.028	0.033	0.394
Liking for Suburban Living	0.060	0.030	0.05
Stressful commute with congestion	0.010	0.031	0.743
Liking for Outdoor life	0.042	0.027	0.121
Pro-technology	0.023	0.030	0.443
Not Active Lifestyle	-0.016	0.032	0.604
Liking for store shopping	0.023	0.030	0.44
Have need for a vehicle	-0.008	0.026	0.772
Time utilization in Congestion	0.033	0.028	0.249
Population density	0.022	0.034	0.529
National Walkability Index	-0.017	0.009	0.052
Place type (Base: Urban)			
Suburban	0.077	0.084	0.359
Rural/Non-urban	0.130	0.217	0.548
Constant	9.350	0.364	0