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Behavioral Realism of Plug-In Electric Vehicle Usage: Implications for Emission Benefits, Energy Consumption, and Policies

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Behavioral Realism of Plug-in Electric Vehicle Usage:
Implications for Emission Benefits, Energy Consumption, and Policies

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Abstract

Accelerating the adoption of plug-in electric vehicles (PEVs), is critical to reduce GHG emissions in the light duty vehicle sector. Conventional PEV usage and GHG assessments are largely based on assumptions drawn from stated preferences and choice experiments of potential or current PEV owners, or self-reported travel and refueling diaries of mainstream internal combustion engine(ICE) users. This dissertation focuses on observed behavior of current PEV users. I present three studies that seek to improve our understanding of PEV driving and charging typified by two levels of disaggregation- vehicle level and household level.

First study develops an analytical procedure to quantify what aspects of driving and charging behavior contributes to the gap between observed PHEV Utility Factors and Society of Automotive Engineers (SAE) J2841 expectations. Results indicated that depending on the PHEV range, roughly ±45% of deviations is attributable charging behavior. Daily mileage was responsible for -20% to +3% of deviation. Annual mileage and effective charge depleting range achieved on-road influenced the UF deviation by ±25% and -20% to -4% respectively.

In the second study, driving and charging behavior differences between short-range (20 miles or less) and long-range (35 miles or more) PHEVs are investigated. It was found that diversity of charging locations is positively associated with electric miles from short-range PHEVs whereas encouraging more home charging increases the electrification benefits of longer-range PHEVs.

Third study quantifies the well-to-wheel GHG mitigation potential of Nissan Leaf, Chevrolet Bolt and Tesla Model S at the household level using a multi-year actual usage data from 73 two-car (single BEV and single ICE) California households. Analysis shows that on average 25% of Leaf and Bolt, and 30% of Tesla household's GHG can be reduced from their current levels by driving the BEV instead of the ICE. Upgrading to a longer-range efficiency oriented BEV and fully charging overnight can mitigate an additional 10-15% household GHG. Upgrading to longer-range sportier performance oriented BEV nearly offset the GHG abatement benefits, but it electrifies the highest share of household miles.

Acknowledgements

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I would like to thank my colleagues at the PH&EV center, Scott Hardman, and Debapriya Chakraborty. I would like to acknowledge and thank the California Air Resources Board and California Energy Commission for supporting the Advanced Plug-in Electric Vehicle Travel and Charging Behavior (eVMT project). Special note of mention and thanks to Vaishnavi Karanam, Katrina Sutton, Matthew Favetti, and Chris Nitta.

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I dedicate this dissertation to my parents Vasumathi and Srinivasaraghavan, and my sister Sandhya for their patience, unwavering faith in my abilities, and their collective sacrifices.

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1 Background and Motivation

Road transportation accounted for 23% of global Greenhouse Gas (GHG) emissions and 28% of GHG emissions in the U.S [1, 2]. In 2018, California's total GHG was 430 $MMTCO_2e$ (million metric tons of Carbon-di-Oxide equivalent), of which the light duty vehicle(LDV) share of transportation sector emissions was approximately 30% [3]. Accelerating the adoption of battery electric (BEVs) and plug-in hybrid electric vehicles (PHEVs), collectively addressed as plug-in electric vehicles (PEVs), is a vital element in California's long-term strategy to reduce GHG emissions from the LDV sector. California has adopted a comprehensive suite of policies to increase the market penetration of PEVs as part of its Advanced Clean Cars program[4]. Technology forcing Zero Emission Vehicle(ZEV) mandate[5], demand side purchase incentives,[6, 7] , and investments in charging infrastructure [8] have played a major role in enabling the state to lead the U.S. in terms of PEV market share{VELOZ, 2018 #1024}[9].

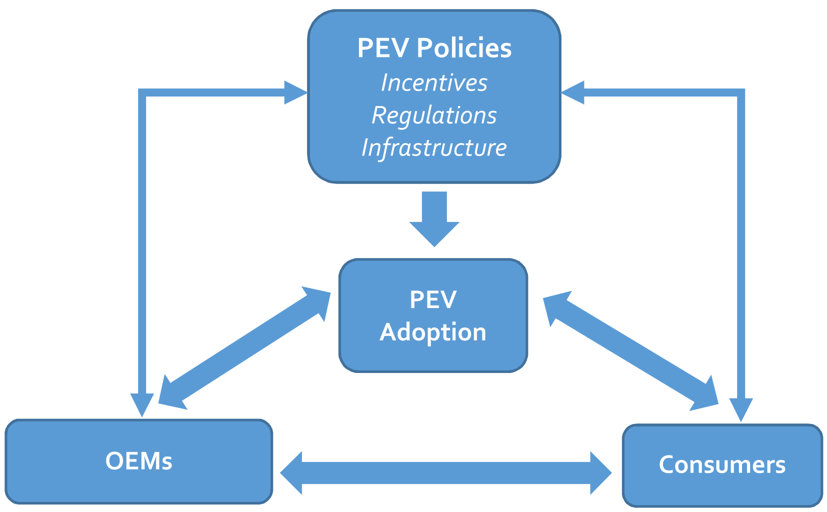


Figure 1.1 Stakeholders in PEV Adoption

Figure 1.1 depicts the important stakeholders in growing the PEV–original equipment manufacturers (OEMs) of cars and electric vehicle supply equipment (EVSE), policy makers, and the PEV buyers. Studies have shown that states with ZEV mandate tend to have higher PEV model choices and sales [10]. There is also a positive relationship between demand side incentives such as rebates and tax credits and charging infrastructure accessibility on PEV adoption [11-13]. While such studies bode well for understanding the effectiveness of policies on PEV adoption [14] and capturing factors that influence PEV purchase decisions, the net environmental benefits of PEVs depend on the extent to which they are actually used, and their typical daily driving and charging needs.

Understanding daily driving needs is crucial for automakers to better align their PEV model offerings, design, and performance attributes with consumer needs. Understanding when, where and how long PEVs are charged and what is the anticipated charging demand are important for charging infrastructure developers from cost recovery, charger accessibility, and charger utilization perspectives. Utility companies are particularly concerned about PEV charging patterns as it has the potential to create localized hot spots if not managed properly, necessitating network upgrade or expansion[15]. Utility companies can also design their PEV rates to incentivize charging during off-peak hours. Consumer's perceptions on the ability of PEVs to meet their daily driving needs , higher upfront capital cost compared to ICEs, range anxiety, and reliable access to charging infrastructure continue to be major barriers to large-scale PEV adoption[16-19]. These barriers create uncertainties in the evolution of PEV market. Heterogeneities in daily driving patterns and needs across various sociodemographic indicators and household factors, further compound these uncertainties. From the perspective of policymakers, information about PEV usage is extremely valuable to quantify gasoline displaced and GHG reduction potential. In addition, it will offer insights into the barriers and opportunities to increase the environmental benefits of PEVs in the long- run.

Prior research advocates the need to have realistic representation of PEV usage to increase their usefulness to policymakers. There is a good chance of overestimating emission reduction benefits from PEVs by relying on data from travel diaries due to the inherent biases [20], room for up to 25% underreporting of trips[21], and underreporting of long-distance travel [22] compared to GPS tracked studies. Given the relative scarcity of actual PEV usage data, researchers and policymakers create scenarios by combining various sources of travel data and superimposing a set of preconceived expectations about PEV driving and charging needs. These expectations about their driving and charging behavior are used to benchmark their energy consumption and emissions, which have consequential impacts on specific policies that rely on them such as credit allocation under the ZEV mandate [23] and PEV infrastructure projections and investments[8, 24].

An often ignored or inadequately addressed issue in contemporary PEV usage studies is the household context. Considering that household factors (vehicle ownership, size, and number of drivers) impact vehicle type choice, vehicle usage, and household travel demand [25, 26], studying PEV usage in isolation may lead to inaccurate estimates of their net environmental impacts, since it is based on partial information. By using average daily distances as an objective metric to determine the feasibility of PEV to replace an ICE ignores the subjective behavioral changes necessitated by the adoption of PEV [27]. BEVs have entirely different recharging patterns compared to refueling behavior of ICEs. Assuming homogenous usage of a specific PEV model across diverse strata of demographics and travel needs, and subsequently their emission reduction potential presents an inaccurate picture of the day-to-day substitution patterns between an ICE and PEV, since it depends on household factors and vehicle attributes. Even if high resolution data from actual PEV usage is available, it is necessary to observe them over a considerably longer duration of time compared to few weeks or months to capture the full spectrum of trip and daily miles driven. Therefore , for a realistic assessment of their GHG benefits, it is important to gain a better understanding of the dynamics of actual PEV usage.

1.1 Research Context

Expectations versus Experience aptly portrays the central theme of my dissertation – i.e. what we expect PEV users to do and usage patterns to be versus how PEVs are actually used in real-world. Analytical insights and policy implications presented in this dissertation are based on the refueling/recharging data of PEVs observed and collected as part of the *Advanced Plug-in Electric Vehicle Travel and Charging Behavior* (eVMT project)[28-30]. The eVMT projects aims to understand the driving and charging needs, emissions potential of plug-in electric vehicles (PEVs) under real world conditions, highlight the opportuntities and challenges, facilitate discussions and help inform future PEV policies.

1.2 Research Objectives

At the highest level, this dissertation seeks to answer two questions– *i) what and how much do we know about the actual PEV usage, especially their driving and charging needs? and ii) what and how much do we know about PEV usage in the context of household travel?* The overarching goal is to improve our understanding of PEV driving and charging needs, provide an opportunity to scrutinize the consequences of revealed behavior deviating from assumptions and expectations on PEV policies, and leverage the insights to better inform future PEV policies. Specific research questions answered include:

- Why real-world utility factors of PHEVs differ from window sticker label expectations?
- How user preferences are reflected and distinguished between electrification potential of short-range and longer-range PHEVs?
- What is the current and prospective GHG mitigation and electrification benefits of BEVs at the household level?

1.3 Dissertation structure

This dissertation is organized as follows:

Chapter 1 provided the background and motivation and sets the context of this research.

Chapter 2 examines the reasons attributable to real-world Utility Factor(UF) of PHEVs deviating from sticker label expectations. An analytical procedure is developed and applied on driving and charging dataset of 153 PHEVs which includes – 1st generation Toyota Prius (11 mile range), Ford CMax and Fusion Energi (20-miles), 1st generation Chevrolet Volts (35/38 mile range), and 2nd generation Chevrolet Volts(53 miles).

Chapter 3 further builds upon this study and deduces eight characteristic driving and charging profiles of short-range (20 miles or less) and longer-range PHEVs (35 miles or more) that capture charging accessibility by location, charger utilization by frequency and duration of charging, driving style, and long distance travel needs. The relative importance of each of these profiles on the real-world electrification potential and how it varies between short-range and longer-range PHEVs are examined.

Chapter 4 quantifies the current electrification and well-to-wheel GHG benefits of BEVs in 2-car households. The implications of travel day vehicle selection, overnight home charging, and BEV attribute upgrade on electrification of household travel and resulting GHG abatement potential are examined. This chapter discusses the interlinkage between user preferences and BEV range and how it manifests in the substitution potential of BEVs. Role of ICE class and future BEV attributes are discussed from the perspective of infrequent travel needs and its contribution to the share of hard to abate GHG. Concluding remarks and future research directions are presented in Chapter 5.

2 Plug-in Hybrid Electric Vehicle Utility Factors: Observed and SAE J2841 Expectations

2.1 Background

Light duty vehicle (LDV) electrification is a promising solution to mitigate the adverse impacts of GHG emissions on the environment and public health. Plug-in hybrid electric vehicles (PHEVs) are often considered a viable option to catalyze the transition towards LDV electrification [31, 32]. PHEVs are equipped with a larger battery pack compared to conventional hybrid vehicles (HEVs) that can be charged using grid electricity and have an internal combustion engine (ICE). PHEVs are not limited by the range of the battery and combine the advantages all-electric capabilities of a battery electric vehicle (BEV) with the engine downsizing, minimal energy losses due to no engine idling, and regenerative braking capabilities of a HEV. PHEVs are operated in two distinct modes: charge depleting (CD), when electrical energy stored in the battery after charging is used to propel the vehicle and charge sustaining (CS) mode in which the PHEV is driven on gasoline.

Charge depleting (CD) mode can be categorized into CD-EV and CD-blended (CDB) modes. In the CD-EV mode of operation, the entire traction energy is met by discharging the energy stored in the battery. The vehicle is driven in all-electric mode by the motor and the engine is never turned on. This type of operation is called EV-mode, all-electric mode, or zero emission (ZE) mode because only electricity is consumed and there are no tail-pipe emissions. Depending on the powertrain configuration, road network topology, speed and acceleration characteristics, in the CD mode, engine may turn on to partially assist the motor in meeting the total energy demand at the wheels. This is called CDB mode of operation because both electricity and gasoline are consumed. The CD mode of operation continues until the battery is fully discharged, after which the PHEV is operated in the CS mode as a regular HEV with the ICE providing the propulsion energy and only gasoline is consumed. Operational and fuel use flexibility enables PHEVs to substitute gasoline partially or completely with electricity. It is this same attractive design feature that makes the exercise of characterizing PHEV emissions and energy consumption quite challenging. The test procedures for estimating their environmental performance need to combine both modes of operation.

The distance driven in either CD or CS modes depends on battery capacity, electrical energy consumed in the CD mode, distribution of trip lengths and frequencies, and the recharging frequency. A key performance metric of PHEVs from the perspective of gasoline displacement, GHG emissions, and local criteria pollutants is the fraction VMT electrified, also known as Utility Factor (UF). At a conceptual level as the name implies, it denotes the limited utility of the CD mode of operation until the battery is fully depleted, hence called Utility Factor. Society of Automotive Engineers (SAE) J2841[33] formally defines the UF and outlines recommended procedures to calculate the UF. Utility Factor essentially weighs the share of distance driven in CD and CS mode of operation relative to the total distance traveled and is expressed as a ratio between 0 and 1. These weights are incorporated into the test procedures for estimating combined fuel economy, and mode specific emissions and energy consumption according to the SAE J1711[34] standard.

PHEVs are typically denoted as PHEVX, where “X” is the Charge Depleting Range (R_{CD}) or simply range in miles, where R_{CD} is the distance traveled by a fully charged PHEV in the CD mode before the battery is completely depleted. The vehicle miles traveled (VMT) in the CD mode could be comprised of VMT on electricity (eVMT) only or electricity and gasoline (gVMT), whereas CS mode involves only gVMT. There are four different definitions of range in the SAE J1711–All Electric Range (AER), CD Cycle Range, CD Actual Range, and Equivalent All Electric Range. The AER of a PHEV is the total distance traveled from the beginning of a Full Charge Test (FCT) to the point when the first engine turn-on event occurs. The CD cycle range (R_{CDC}) is the distance traveled either completely (no engine turn-on) in the CD-EV mode or partially in the CDB mode under a test-cycle until the battery is completely depleted. The CD cycle range is the sum of the distances traveled from the beginning of an FCT up until the end of the last test-cycle(s) prior to the cycle meeting the End-of Test (EOT) criterion including the transition range where the engine might momentarily turn on though the battery is not fully depleted. The EPA label lists the AER and R_{CDC} for applicable PHEV models. Full Charge Test as the name implies requires that the test begin with the battery state of charge (SOC) of 100% and transition range is the distance traveled between the CD and CS modes. Since the exact determination of the point at which the transition between CD and CS modes occur, the SAE J1711 employs analytical method to determine the CD actual range (R_{CDA}) which is always less than or equal to the R_{CDC}. The Equivalent All Electric Range (EAER) is the fraction of CD cycle range attributable to grid electricity and is equal to greater than the AER.

The J2841 UF definitions for PHEVs explicitly assume that:

i) travel day starts with a fully charged battery.

ii)PHEV is charged once per day on days driven after the end of last trip.

iii)impact of additional intra-day charging, and vehicle not being charged at the end of travel day offset each other equally, and

iv)travel patterns of PHEVs are identical to the single-day trip diary information of ICEs in the 2001 National Household Travel Survey (NHTS).

These assumptions have widespread ramifications on energy and emissions estimates of PHEVs embodied in existing policies, charging infrastructure planning, and electricity grid impact studies [14, 24, 35-37]. In the policy domain, the significance of the UF cannot be understated since it is the critical metric assessed for many policies in the U.S. including the Environmental Protection Agency (EPA) fuel economy labeling or window sticker [38, 39], credit allocations under California's Zero Emission Vehicle (ZEV) mandate and Low Carbon Fuel Standard [40], and compliance with fuel economy and emission standards [41-43]. Though the SAE J2841 was developed from a U.S. centric perspective, at a methodological level, the concept of UF, core assumptions on charging behavior, relying on national driving statistics to represent PHEV driving patterns, and a standardized procedure to calculate the UF has been adopted by regions outside the U.S. as well, albeit with few region specific modifications to the test cycles and driving database. China's LDV fuel economy standards and energy consumption and emission estimates for type approval in European Union [44, 45], to name a few.

The assumptions outlined in the J2841, though plausible, may not reflect how actual PHEV owners drive and charge their vehicles. Prior work in this area focused on alternative UF calculated using different cross-sectional or longitudinal travel survey datasets, incorporating additional charging scenarios, and performing sensitivity analysis of UF to various vehicle and sociodemographic attributes [41-43, 46-48]. More recently, with the availability of observed driving and charging data through on-board telematics and data-loggers [49-55], estimating on-road emission mitigation potential and characterizing driving and charging patterns [56-60] are other areas where analysis of UF is pertinent. UF has also been widely used in evaluating the life-cycle costs, emissions and value proposition of PHEVs [61, 62], and optimal battery size design and its impact on market acceptance [63, 64].

In summary, many studies have been carried out to assess validity of J2841 UF assumptions on charging and driving by simulating different scenarios and comparing simulated UF to their theoretical J2841 UF equivalent. However, a straightforward approach that uses observed driving and charging behavior to reconcile their deviations from J2841 UF expectations is found lacking. To the best of my knowledge, no study attempted to delve deep into how key driving and charging traits such as annual VMT; daily VMT (DVMT) distribution and range utilization; charging behavior; and effective range achieved on-road, affect the disparities between observed UF and J2841 UF. Data availability of actual PHEVs is still scarce compared to the publicly available travel survey data of conventional ICEs. Even though observed data is valuable and desirable since they represent PHEV usage better compared to surveys, policy recommendations cannot be tailored and altered depending on the availability and quality of actual PHEV usage data. Therefore, it is necessary to interpret the UF observed in terms of the standardized UF. This chapter addresses these two areas of need in the context of UF of PHEVs using year-long GPS enabled driving and charging data of 153 PHEVs (11-53 miles range) in California.

The objectives of this study are:

i) quantitatively and qualitatively understand the deviations in observed UF from J2841 UF.

ii) identify vital aspects of driving and charging that cause these deviations and ;

iii) systematically estimate the direction and magnitude of impact individually attributable to these aspects.

The outcomes of this work will augment policy insights gathered from contemporary efforts and elucidate how observations about PHEV usage today can better inform future vehicle design and policy needs. This study contributes to the evolving field of improving the accuracy of UF estimates to enhance PHEV emissions reduction benefits and market penetration. Furthermore, the methodology outlined in this chapter is intended to serve as a template for similar comparisons of PHEVs performance in different locations and settings using different standards. Rest of the paper is organized as follows. In Section 2.2, I briefly review the background of the standardized J2841 UF and the alternative definitions considered in literature. A concise overview of its developments in the European Union(EU), South Korea, Japan, and China is also presented in Section 2.2. Section 2.3 provides an overview of the data and analytical methods employed in this chapter to quantify deviations between observed and J2841 UF. Results are elaborated in Section 2.4. Research outcomes and its applicability are synthesized in Section 2.5.

2.2 J2841 UF in practice and its variants

The foundational and procedural aspects of the SAE J2841 UF within the U.S. context is presented. I expand the scope and provide an overview of its how its estimated outside the U.S., in EU, South Korea, Japan, and China and summarize contemporary literature on UF and its variants.

2.2.1 Conventional J2841 UF definitions

The J2841 UF is calculated based on the trip and daily VMT distribution of mainstream ICE users in the U.S. represented in the 2001 NHTS, here after addressed as just NHTS[65]. The NHTS trip diary information captures a one-day snapshot of travel patterns self-reported by survey respondents. The raw trip file has close to 642,000 trips and the following filters are applied in order to calculate the UF: i) subject was driver on this trip (DRVR_FLG=1); ii) national sample (SMPLSRCE=1); iii)non-zero trip miles and duration (TRPMILES and TRVL_MIN > 0) and ; iv)only light duty vehicle trips (VEHTYPE is 1-4) are selected. DVMT is obtained by summing the trip distance and time for each unique household and vehicle used and roughly 32,000 vehicles or vehicle-days are in the filtered subset. Let $d(k)$ denote the distance traveled on travel day k. The VMT weighted daily distance based UF according to the J2841 methodology is calculated as follows: If $d(k) > R_{CD}$, then UF =1 and $R_{CD}/d(k)$ otherwise. For a travel dataset with N days, the same logic is extended and the UF for a specific range is calculated according to Eq.(1).

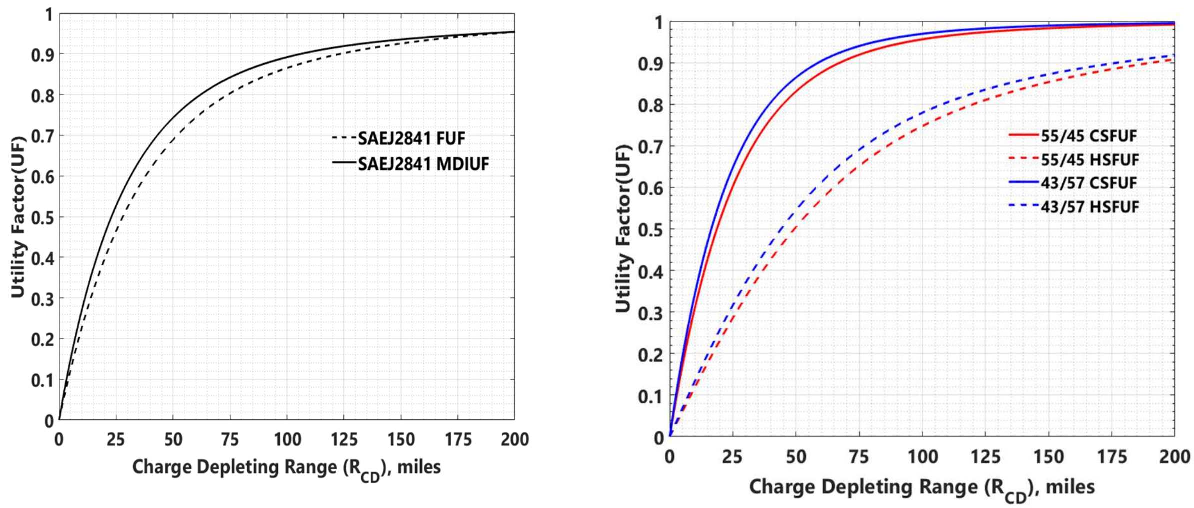
$$\mathrm{UF}(R_{CD}) = \frac{\sum_{k-1}^{N} \min(d(k), R_{CD})}{\sum_{k-1}^{N} d(k)} \tag{1}$$

The VMT weighted UF described in Eq. (1) is called the Fleet Utility Factor (FUF) since represents the UF of an entire fleet of PHEVs. The numerator and denominator in Eq. (1) are the total eVMT and VMT of the fleet. The FUF represents the fraction of total miles in the NHTS fleet driven in the CD mode. In some instances, it might be desirable to convey information for an average PHEV since the VMT weighted FUF is biased towards long-distance trips. For this purpose, the Individual Utility Factor (IUF) is used which is the vehicle weighted UF. The basic approach to calculate the IUF is same as that of the FUF. Let N_{Days} and $N_{Vehicles}$ denote the number of days and vehicles in the dataset and $d_{(i,j)}$ denote the distance traveled by vehicle i on travel day j. The IUF is calculated according to Eq. (2). The IUF represents the arithmetic mean of the fraction of miles driven in CD mode over $N_{Vehicles}$. Depending on the whether the dataset has information about Single Day (SD) or Multiple Days (MD) of travel, the IUF calculated is expressed as SDIUF or MDIUF. The Commute Atlanta dataset[66] was used as a supplementary dataset to calculate the MDIUF but the FUF and IUF distribution was found to be the same between them.

$$IUF(R_{CD}) = \frac{\sum_{i=1}^{NVehicles} \frac{\sum_{j=1}^{NDays} \min\left(d_{i,j}, R_{CD}\right)}{\sum_{j=1}^{NDays} d_{i,j}}}{NVehicles} \tag{2}$$

Since energy consumption is a function of driving speed, the J2841 method includes two methods to create FUF that are conditional upon driving style: City Specific (CSFUF) or Highway Specific (HSFUF). In the first method, average trip speed is calculated, and the entire trip is categorized as city or highway driving based on a cut-off speed. The conventional assumption on the split between city and highway driving is 55/45 [67] and the cut-off speed to obtain this is 42 mph. Trips with average speed greater than 42 mph are designated as highway driving and assigned a highway weight of 1 and city weight of 0 and vice-versa for the remaining trips designated as city driving. The second method selects two cut-off speeds to define city only and highway only. Trips with average speed below 25 mph or above 60 mph are categorized as city only and highway only respectively. The city/highway weight assignment is like the first method. For trips with average speed between the two cut-offs, the city/highway weight is linearly scaled between 0 and 1, wherein the weight for city driving decreases from 1 with increasing speed beyond 25 mph and vice-versa for the highway driving weights. These trips are considered to have an equal likelihood of being city or highway style driving. At a travel day level, daily weights for city driving and highway driving are calculated based on the method chosen and the share of distance traveled in the respective driving style as a ratio of the total daily distance traveled. The dataset is divided into city and highway driving styles and the UF is estimated according to the basic form shown in Eq. (1). The J2841 method applies exponential fits to the generate FUF and IUF curves, Eq. (3), where x is the R_{CD} , C_i is the fit coefficient, j is 6 for FUF and 10 for IUF, and D_n is the normalized distance (400 miles in the U.S.). The J2841 FUF and MDIUF, CSFUF and HSFUF curves are shown in Figure 2.1(a) and Figure 2.1(b)respectively.

$$UF(x) = 1 - exp\left[-\left(\sum_{i=1}^{j} C_i \left(\frac{x}{D_n}\right)^i\right)\right] \tag{3}$$



(a) U.S. (b) U.S.

Figure 2.1 top left (a) U.S. J2841 FUF and MDIUF curves; top right (b) U.S. J2841 CSFUF and HSFUF curves for 55/45 and 43/57 city/highway driving splits

2.2.2 Utility Factor developments and applications internationally

The concept of UF, its purpose as a weighing factor and as an indicator of the environmental impact of PHEVs, and the basic procedure to estimate the UF outlined in the SAE J2841 is also used as guideline to calculate energy consumption and emissions of PHEVs outside the U.S.. To account for the country-specific driving patterns and prevailing regulations, representative national driving statistics, test cycles, and testing procedure used outside the U.S. typically differ from the conventional SAE J1711 and SAE J2841 approach. Quality, sample size and resolution of national driving database, pre-conditioning requirements (for example soak time and temperature, test site conditions), end-of-test criterion, number of test cycles used for CD range determination, and city/highway driving split are some of the aspects that varies outside the U.S. in regards to UF determination and regulatory assessment of PHEVs[68]. A detailed cross-country comparative assessment of UF estimations is outside the scope of this study, therefore I limit the review of international studies to highlighting only its key features.

In the U.S. two test cycles are used Urban Dynamometer Driving Schedule(UDDS) and Highway Fuel Economy Test (HWFET) cycle, whereas in the EU, only one test cycle, namely the Worldwide Harmonized Light-duty vehicle Test Cycle (WLTC) and its associated Worldwide Harmonized Light-duty vehicle Test Procedure (WLTP) are used [44, 69]. Prior to the introduction of WLTP in 2017, New European Drive Cycle (NEDC) was used the test cycle for type approval[70] but was phased out in favor of the WLTP in order to reduce the gap between on-road and type approval energy consumption and emission estimates. Realistic driving behavior, inclusion of diverse driving situations (urban, suburban, main road, and motorway), representing high speed and propulsion power demand, and stringent testing conditions are some of the notable benefits of the WLTP compared to the NEDC [71]. The CD range estimated based on the NEDC is reduced by 25% under the WLTP[72]. Measurements using the WLTP also considers optional equipment and add-ons for comfort, luxury, and performance that impacts the rolling resistance, vehicle aero-dynamics, and mass[73].

The WLTP is sub-divided into four-phases (low, medium, high, and extra high) with the average speeds increasing with each subsequent phase representative of urban (up to 35 mph) , suburban (up to 47 mph), main road(up to 60 mph) , and motorway (up to 81 mph) driving, respectively. Energy consumption (fuel and electricity) is calculated in each phase and aggregated based on the phase specific UF also known as fractional UF, to determine the combined energy consumption. Currently two datasets are available in the EU to obtain representative driving patterns – European WLTP database which was used to develop the WLTC and the driving data provided by FIAT[69]. The single overnight charging at home and travel day starting on a fully charged battery assumption is retained in the WLTP for UF estimation in the EU. The WLTP allows EU member nations to develop their own UF curves.

In Japan, prior to 2020, JC08 was the official test cycle, which is set to be replaced by the WLTP as part of its 2030 fuel economy standards for LDVs[74]. The procedure to estimate the UF of PHEVs in Japan is identical to that of the EU’s approach discussed above. China is currently developing its own LDV test cycle called the China Light-duty vehicle test cycle (CLTC) and it is expected to be the norm from 2023 onwards. Between now and 2023, the WLTP will be used for estimating the UF. South Korea follows the SAE J1711 testing procedure and SAE J2841 for UF estimation[75, 76].

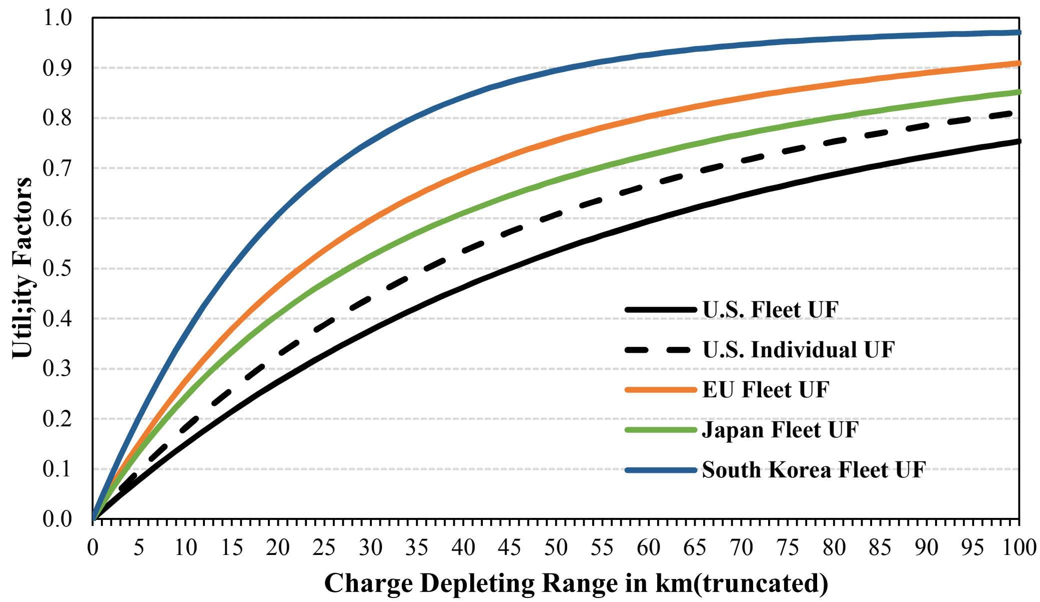


Figure 2.2 U.S., South Korea, WLTP based EU, and Japan UF Curves

Eq. (4) shows the WLTP based approach for UF estimation in the EU where – $UF_j(x_p)$ is the fractional UF for phase p, x_p is the distance driven in km from the beginning of the full charge test to the end of phase p, C_j is the jth coefficient, k is the order of the exponential fit (10 in EU, 5 in South Korea and 6 in Japan), D_n is the normalized distance, set at 800 km, 600 km, 400 km in the EU, South Korea, and Japan, respectively, and $\sum_{l=1}^{p-1} UF_l$ is the sum of calculated UF to phase *p-1*.

$$UF_j(x_p) = 1 - exp\left[-\left(\sum_{j=1}^{k} C_j \left(\frac{x_p}{D_n}\right)^i\right)\right] - \sum_{l=1}^{p-1} UF_l \qquad (4)$$

Figure 2.2 depicts the UF curves generated for the U.S., and WLTP based Fleet UF curves for EU, Japan, and South Korea. Because of the transition to WLTC and WLTP in many countries outside the U.S., only the generic procedure to estimate the UF using the WLTP in the EU was elaborated. The fit coefficients used for estimating the UF in the U.S, South Korea, EU, and Japan are summarized in Table

A1 of Appendix A. Cross-country comparison of key test cycle parameters (speed, distance, acceleration) is summarized in Table A2 of Appendix A.

2.2.3 Alternatives to the conventional UF and empirical evidence from observational studies

Bradley and Davis explore alternatives to the J2841 UF using the 2009 NHTS instead of the 2001 NHTS [42]. In addition to end of travel day charging, a mid-day opportunistic charging scenario is also considered. The authors report that the alternative UF is higher than the J2841 UF for ranges less than 65 miles. In [43], sensitivity of the J2841 UF to charging behavior, dwelling unit type, fuel economy, vehicle usage intensity, vehicle age, and vehicle type (passenger cars versus SUVs, vans, and light duty trucks) is studied. An energy based UF is proposed is also proposed in [43]. Their analysis shows that UF is highly sensitive to charging behavior, vehicle age and vehicle usage intensity but insensitive to vehicle class, fuel economy and dwelling unit type. Longitudinal travel data collected over a span of 18 months via GPS devices installed in approximately 400 ICEs operating in the Seattle metro area data is used in [77] to compare UF estimated under different gasoline and electricity prices, type of day (weekday and weekend UF) and the availability of workplace charging. Their study explores how the UF changes if only home-based tours are considered compared to considering the entire distribution of VMT. Authors in [77] report that UF estimated using the Seattle travel dataset is higher than the conventional J2841 UF, fuel and electricity prices have no significant impact on the UF, and if only home charging is available, UF is not sensitive to travel patterns and charging behavior. Paffumi et. al. in [78] conclude that the J2841 UF method sufficiently captures the driving and charging behavior of PHEVs using GPS data of ICEs from six European cities. Their study mentions that future UF estimates should be capable of handling heterogeneous preferences in charging location, timing, and frequency.

With advances in telematics data acquisition, big data analytics, and support for regional and nationwide PHEV demonstration projects such as the Idaho National Laboratory(INL) EV Project [53-55], increasing efforts have been made to assess the performance of PHEVs by observing their actual usage. In [53], it is reported that the observed FUF of 1400 Model Year (MY) 2011-2013 Chevy Volts was higher than their J2841 FUF estimates by 6%. A similar study of close to 50,000 MY 2011-2014 Chevy Volts in [56] report that the observed Volts were able to travel 74% of their total miles in EV mode alone without turning on the engine. The recent midterm review of the Advanced Clean Cars program by the California Air Resources Board (CARB) analyzed driving and charging data provided by the automakers and it was found that the observed FUF of Ford PHEVs with 20 mile range was lower than the J2841 FUF estimates by 4-6% and the observed FUF of Toyota Plug-in Prius PHEVs with 11 miles range was lower than the J2841 FUF by 8% [40]. Researchers in Germany [79] analyzed the real-world fuel economy and UF of 2000 PHEVs with 11-38 miles range and conclude that the deviations in observed fuel economy varied from the estimates based on standardized drive cycles could be anywhere between 2% to 120%. In [80] supervised and unsupervised machine learning techniques are applied to predict the UF of 1800 Chevrolet Volts. Analyses indicated that the variance and skewness of the daily VMT distribution and frequency of long-distance travel are better predictors of UF compared to assuming a single charging event per day[80].

Utility Factors of various PHEV models reported in related studies in the U.S. and EU alongside their label expected UF is compiled and presented in Table A3 of Appendix A. Literature review indicated that depending on the region and data acquisition method (in-use observational, aggregated telematics data from the OBD port, or surveys), the UF of 11-mile Prius and 20-mile Energi PHEVs could differ from label UF by +30 to -66% and -4% to -50% respectively. The UF of first generation 35/38-mile range Volt could be +7% to 30% more than the label UF, whereas the second generation 50-mile range Volt's UF varies from label UF by -5% to +40%(Table A3, Appendix A). To summarize, the type of travel survey (stated or observed preferences), duration of data-collection, mode of data acquisition (self-reported trip diaries, data loggers with or without GPS), type of vehicle(s) used for data collection, survey population (mainstream ICEs or actual PHEV owners), and assumptions about charging behavior will have consequential impacts on our understanding of PHEVs and their role in personal transport electrification.

2.3 Data and Methods

The source of the data used is from the Advanced PEV Driving and Charging Behavior project, a multi-year study to monitor PEV usage in California [29, 81]. This project consists of an online survey of current PEV buyers in California followed by a yearlong data collection study of a sub-sample of respondents. Data loggers that collect a second by second data on the vehicle energy use and travel characteristics were installed to understand how current PEVs being used a day to day basis. Online survey details is outlined followed by the logger data acquisition and post processing steps involved .

2.3.1 Online Survey Data

Participants for the online survey were recruited randomly from the California Clean Vehicle Rebate Project (CVRP) data and the California Department of Motor Vehicles (DMV) records [82]. Stratified random proportionate sampling strategy was primarily used to recruit participants. Stratification was based on the five major utility companies(investor and publicly owned). Investor owned utilities (IOUs) are Pacific Gas & Electric (PGE), San Diego Gas & Electric (SDGE), and Southern California Edison (SCE). Sacramento Municipal Utility District (SMUD) and Los Angeles Department of Water and Power (LADWP) are the two public owned utilities (POUs). California Air Resources Board emailed survey invitations to people who applied CVRP and sent postcards to people randomly selected from the DMV registration data who did not apply for the CVRP. Close to 19,000 PEV owners were recruited between April 2015 and Nov. 2017. 12,396 of the respondents indicated that they are willing to participate in the GPS logger study. The overall response rate for the survey was 18% and 75% (14,000) of these respondents completed the survey. The study population is the list of people who purchased their PEV in the last 4 years. The sampling frame is the list of current PEV owners in CVRP database and the DMV records in the state of California. Apart from the socioeconomics, demographics, vehicle ownership, household size, information about charging behavior (location, charger level, charging frequency, membership with charging networks, perception of charger access at different locations) and driving behavior in the last 30 days and the past week , electricity provider, availed incentives, self-reported annual vehicle miles traveled, and how would they have changed their driving and/or charging behavior under different prices and charger availability at different locations were obtained.

As it is true with similar real-world observational studies of PHEVs [10, 18, 54, 80], cross-population generalizability of this study's findings is limited by the small sample size. PHEV users in this study are early adopters who have unique sociodemographic characteristics (higher income, more educated, more likely to own rather than rent housing), behavioral patterns, and travel needs that may also differ from conventional ICE users[9, 10]. Correlation among socio-economics and demographic indicators and self-selection bias of PEV owners is inherent and it is prohibitively expensive (data collection period, travel logistics associated with logger installation and uninstallations, and staff hours) to control for every such correlation[17, 83]. Despite the small sample size of vehicles, the PHEV models considered in this study accounted for 77%[1] of all rebates issued to PHEVs between 2010 and 2018 by California Clean Vehicle Rebate Project[7]. Table A11 of Appendix A presents the proportional share of CVRP rebates issued by utility territory and OEM and the corresponding coverage of PHEVs analyzed in this study. Relevant socio-demographic attributes of the 153 PHEV owners recruited for the logger data analyzed in this study and the 2017 National Household Travel Survey California(CA) add-on[84] participants is summarized in Table A12 of Appendix A.

I used the 2017 NHTS-CA add-on because it is more recent, geographical consistent, and overlaps with the survey administration and data collection timespan of this study. Given the sample and cross-population generalizability limitations, this study does not attempt to project the insights gathered on the larger PHEV market segment in California or nation-wide. As such the results presented here should be comprehended within the early developmental stage of the PHEV market.

[1] On a one-to-one comparison between the PHEV models in this study and the CVRP database. This difference is due to 25-mile range Prius Prime PHEV launched in 2017, which was excluded when comparing the proportional shares. If we use the OEM, then the OEMs of the analyzed PHEVs in this study account for 87% of the CVRP rebates issued to PHEVs.

2.3.2 Logger Data Acquisition and Post Processing to Calculate eVMT

FleetCarma C2 or C5 type data loggers [85] were installed in the on-board diagnostics (OBD-II) port of the vehicles. Key driving and charging related variables such as state of charge, distances, engine speed, battery voltages and currents, fuel and electrical energy consumption were collected. The eVMT is calculated based on the methodology outlined in the Idaho National Laboratory's EV project [86, 87]. Every trip is classified along the same lines as described in the above as one of the following types: i) charge-depleting-EV without any engine-turn on event ; ii) charge depleting blended (CDB) which utilizes battery and engine for propulsion ; and iii) charge-sustaining (CS) in which the entire propulsion energy is derived from gasoline. For each PHEV type, the energy efficiency ratio (EER2) between the CS and CD-EV mode of operation is calculated using the official specifications provided in the EPA's fuel economy database[88]. Since it is impractical and computationally exhaustive to calculate this at every possible operating point (every combination of vehicle speed, engine speed, engine torque, motor speed, motor torque, SOC etc.), I used the CD-EV mode kWh/mile and the CS mode MPG numbers from EPA's fuel economy database. The equivalent gasoline displaced, which is the product of trip electrical energy consumed and the EER, is then calculated. In the CD-EV mode, trip VMT and trip eVMT are the same. The blended mode eVMT is calculated by multiplying the trip VMT by the ratio of displaced gasoline to total gasoline consumed (displaced plus consumed gasoline). The trip eVMT is the sum of eVMT in the CD-EV and CDB modes and these are shown in Eq. (5)-(6).

$$Trip\ eVMT(\text{Blended}) = \text{Trip VMT} \times \frac{\overbrace{Trip\ kWh \times \left(\frac{\Delta\text{gallons per mile}}{\Delta\text{kWh per mile}}\right)}^{Displaced\ Gasoline}}{Displaced\ Gasoline + Trip\ Gasoline} \tag{5}$$

$$Trip\ eVMT(Total) = eVMT(\text{CD} - \text{Blended}) + eVMT(CD - EV) \tag{6}$$

[2] Ratio of gallons per mile (CS mode) to electrical energy consumed per mile in CD-EV mode (kWh/mile)

2.3.3 Aggregate Driving and Charging Data

Table 2.1 summarizes the aggregate driving and charging data of the PHEVs analyzed. It includes 153 PHEVs: 22 Toyota Plug-in Prius (11 miles range), 52 Ford CMax and Fusion Energi (20 miles range), 79 Chevrolet Volts (35, 38, and 53 miles range). The driving and charging data consist of 1.95 million VMT, 190,934 trips, 52,223 charging sessions, and 259 MWh of charging energy collected over the course of 44,438 driving days (driving and charging or driving only). Data loggers was installed in the OBD-II port and monitored for at least a year. Out of the 52 Ford PHEVs, 28 were Ford C-Max Energi and 24 were Ford Fusion Energi. Since both have 20-mile range, I combined them into Energi. The 35 and 38-mile range Volts were combined into First Generation Volts (Gen1 Volt) and the 53-mile range as Second Generation Volts(Gen2 Volt) matching with the OEM's official specifications[89]. On average, every vehicle in the dataset was driven 291 days and among the PHEV models, it varied between 278 and 312 during the data collection period (06/2015-06/2018).

Table 2.1 Driving and charging data aggregate summaries (non-annualized)

PHEV	**Number Vehicles**	**Driving Days**	**Number of Trips**	**Total VMT**	**Total eVMT[&]**
Prius	22	6870	31473	314231	46117
Energi	52	14435	64076	667656	229926
Gen1Volt	43	12523	50275	556092	353819
Gen2Volt	36	10620	45110	413687	280390
Aggregate	***153***	***44448***	***190934***	***1951666***	***910253***
PHEV	**Model Year**	**EPA Label R_{CD} miles[88]**	**Number of Charging Sessions**	**Total kWh Charged**	**Charging Sessions/Driving Days***
Prius	MY12-14	11	7661	17606	1.12
Energi	MY12-17	20	19384	70817	1.34
Gen1Volt	MY11-15	35/38	15320	96220	1.22
Gen2Volt	MY16-17	53	9868	74710	0.93
Aggregate			***52223***	***259353***	

* Average number of charging sessions on days driven.
[&]eVMT is the sum of eVMT in CD-EV mode and CDB modes.

Table 2.2 summarizes the average annualized VMT, eVMT, gVMT, and UF of observed PHEVs. The reference annual VMT is based on the EPA sticker label value of 15,000 miles. The eVMT and gVMT calculated from the J2841 FUF and IUF is summarized in Table 2.3. 92% of Prius, 53% of Energi, 47% of Gen1 Volts and 44% of Gen2 Volts charging sessions were at Level 1, up to 1.4 kW [90]. Except for the Gen2 Volts, on average all the other PHEVs charged more than once per day and drove more than 15,000 miles annually and the average annual VMT of the dataset was 15868 miles.

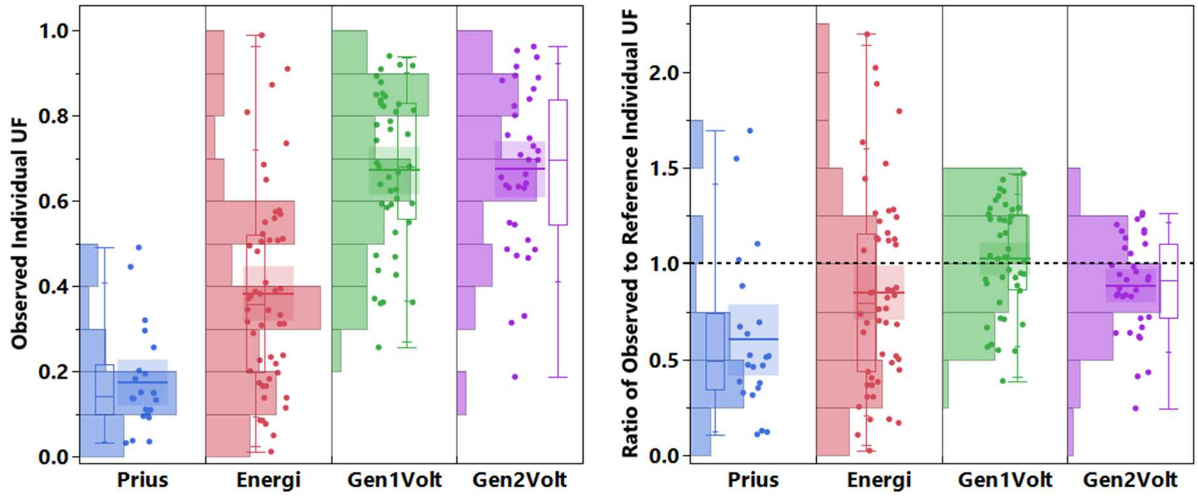
Table 2.2 Observed average annualized driving estimates and UF

	Observed					Fleet UF Gap	Individual UF Gap
PHEVX	**VMT**	**e VMT**	**g VMT**	**IUF**	**FUF**	**FUF_{obs}- FUF_{ref} (ΔFUF)**	**IUF_{obs}- IUF_{ref} (ΔIUF)**
Prius11	16432	2467	13965	0.175	0.150	-0.097	-0.117
Energi20	16705	5554	11150	0.384	0.332	-0.065	-0.072
Gen1 Volt	16038	10273	5764	0.671	0.641	0.053	0.023
Gen2 Volt	14115	9472	4643	0.679	0.671	-0.036	-0.080
Overall fleet	*15868*	*7358*	*8510*				
Mileage annualized based on number of days driven. Observed IUF are vehicle weighed average of UF by definition of IUF, Eq. (2)							

Table 2.3. Reference average annualized driving estimates and UF

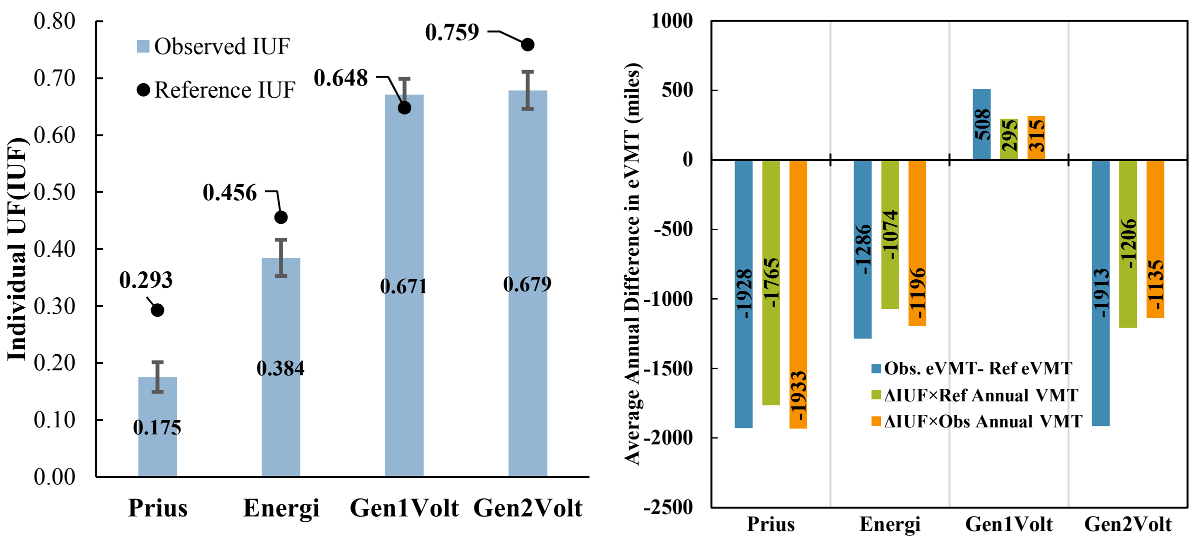
		Reference Fleet			Reference Individual		
PHEVX	**VMT**	**eVMT (FUF)**	**gVMT (FUF)**	**J2841 (FUF)**	**eVMT (IUF)**	**gVMT (IUF)**	**J2841 IUF**
Prius11	15000	3705	11295	0.247	4395	10605	0.293
Energi20	15000	5955	9045	0.397	6840	8160	0.456
Gen1 Volt	15000	8820	6180	0.588	9720	5280	0.648
Gen2 Volt	15000	10605	4395	0.707	11385	3615	0.759

Throughout the rest of the paper unless otherwise specified: J2841 UF and eVMT estimates, NHTS, range and energy consumption found in EPA fuel economy data are addressed as Reference (Ref). Corresponding estimates and dataset of observed PHEVs are addressed as Observed (Obs). VMT, eVMT, and gVMT are annualized averages, range referred is the charge depleting range cycle (for notational simplicity I use R_{CD}), NHTS refers to the 2001 NHTS, and IUF referred is the Multiday Individual Utility Factor (MDIUF). Prius and Energy are collectively addressed as Short-range PHEVs (20-miles or less range) and the Volts as longer-range PHEVs (35- miles or more). Though the classification of PHEV into short or longer-range could arbitrarily differ between studies, it is appropriate resulting in a nearly even split- 74 short-range (22 Prius and 52 Energi) and 79 longer-range PHEVs (43 Gen1 Volt and 36 Gen2 Volt).



(a) (b)

Figure 2.3 (a) Distribution of observed UF of every vehicle in the dataset; (b) Distribution of the ratio of observed UF to J2841 IUF



(a) (b)

Figure 2.4 (a) Average observed IUF and J2841 IUF; (b) Annual eVMT differences between observed and J2841 estimates. Observed IUF are vehicle weighed average definition.

To reinforce the motivation behind this work, refer to Figure 2.3 and Figure 2.4. Fig. 3(a) presents the distribution of the UF of the 153 PHEVs and Fig. 3(b) shows the distribution of the ratio of observed UF to J2841 IUF. Fig. 4(a) shows the observed and J2841 IUF. In this dataset, the IUF of Prius, Energi, and Gen2 Volts was 60%, 84% and 89.5% of their respective J2841 IUF. The IUF of Gen1 Volts was slightly higher than their J2841 IUF by 3%. Fig. 2.4(b) shows the difference in average annualized eVMT between the PHEVs observed and their reference values based on three methods. The first bar for each vehicle type is the raw difference in eVMT found in Table 2.2 and Table 2.3. The second bar multiplies ΔIUF with Reference annual VMT and the third bar multiplies ΔIUF with observed annual VMT, respectively. This further highlights the need and the value of reconciling observed UF in relation to the standardized J2841 UF form to better elucidate their role in LDV electrification. Table 2.4 presents additional summary statistics of the IUF of PHEVs analyzed in this chapter.

Table 2.4 Descriptive statistics of Observed IUF

PHEV	Mean	Std. Dev	Std. Err Mean	95% C.I Mean [Lower, Upper]	Inter quartile Range	Median	Median Absolute Deviation
Prius	0.175	0.121	0.026	[0.122,0.229]	0.115	0.143	0.050
Energi	0.384	0.231	0.032	[0.320,0.449]	0.322	0.358	0.159
Gen1Volt	0.671	0.185	0.028	[0.614,0.727]	0.280	0.681	0.146
Gen2Volt	0.679	0.190	0.032	[0.614,0.743]	0.290	0.697	0.145

2.3.4 Procedure to explore observed IUF deviations from the reference J2841 IUF

The goal of this procedure is to investigate what aspects of driving and charging could be probable reason(s) for Obs UF deviating from the J2841 UF expectations and calculate the individual contribution of each of these sources to the total deviation in UF. Consider Eq.(7) which is obtained from the basic buildup of the J2841 UF shown in Eq. (1) by rearranging the terms and expressing the denominator as the sum of eVMT and gVMT. For the sake of brevity, Eq. (7) is rewritten as Eq. (8), where *e,g,v* denotes the annual eVMT, gVMT, and VMT and similar expression can be written for the observed PHEVs. Disparities between Obs UF and J2841 UF ($\Delta UF = UF_{obs} - UF_{ref}$ could be due to variations in one or more of the following: i) Annual VMT $\left(v_{obs} - v_{ref}\right)$ which in turn manifests as differences in eVMT $\left(e_{obs} - e_{ref}\right)$ and/or gVMT $\left(g_{obs} - g_{ref}\right)$; ii) charging behavior which directly impacts $\left(e_{obs} - e_{ref}\right)$; iii) Daily VMT distribution which influences range utilization and thereby determines eVMT; and iv) Observed charge depleting range digressing from EPA label estimates$\left(R_{CDobs} - R_{CDref}\right)$.

$$UF(R_{CD}) = \frac{\overbrace{\sum_{k-1}^{N} \min(d(k), R_{CD})}^{CD\ VMT\ (eVMT)}}{\sum_{k-1}^{N} \min(d(k), R_{CD}) + \underbrace{\left(\sum_{k-1}^{N} d(k) - \sum_{k-1}^{N} \min(d(k), R_{CD})\right)}_{CS\ VMT\ (gVMT)}} \tag{7}$$

$$UF_{ref}\left(R_{CDref}\right) = \frac{e_{ref}}{v_{ref}} = \frac{e_{ref}}{e_{ref}+g_{ref}} \ ; \ UF_{obs}(R_{CDobs}) = \frac{e_{obs}}{v_{obs}} = \frac{e_{obs}}{e_{obs}+g_{obs}} \tag{8}$$

I break ΔUF into four components to represent the individual contribution of the four aspects to ΔUF. Due to the interrelationship between driving and charging, I consider one aspect at a time and then include the remaining, sequentially. I evaluate the effect of each of the variations individually as difference in eVMT (δ_{eVMT}) and subsequently express these in J2841 UF fraction (δ_{UF}) terms by dividing δ_{eVMT} by v_{ref} as needed. In order to ensure parity and methodologically consistency, I have to first apply the J2841 method, Eq. (1), on the analyzed dataset. Eq. (9) describes the UF, eVMT and gVMT after applying the J2841 methodology.

$$UF_{obs}^{J2841}(R_{CDobs}) = \frac{e_{obs}^{J2841}}{e_{obs}^{J2841} + g_{obs}^{J2841}} \tag{9}$$

Since J2841 assumes that the travel day starts with a fully charged battery, the term $\left(e_{obs} - e_{obs}^{J2841}\right)$ is entirely due to charging behavior observed not aligning with the J2841 assumptions. $\left(e_{obs} - e_{ref}\right)$ can be rewritten as Eq. (10), where $\left(e_{obs}^{J2841} - e_{ref}\right)$ represents the difference between Obs eVMT after applying J2841 method and Ref eVMT. The effect of charging can be further broken down based on whether the PHEVs were unable to use the full range due to inadequately charging or if the PHEVs exceeded the range capabilities by charging more and this is detailed in section 2.4.2. This enables characterizing the net impact of charging as positive or negative depending on the magnitude of δ_{eVMT}(Inadequate Charging) and δ_{eVMT}(Excess Charging), Eq. (11).

$$\left(e_{obs} - e_{ref}\right) = \left(e_{obs} - e_{obs}^{J2841}\right) + \left(e_{obs}^{J2841} - e_{ref}\right) \tag{10}$$

$$\begin{aligned} \boldsymbol{\delta_{eVMT}}(\textbf{Charging}) &= -\delta_{eVMT}(\text{Inadequate Charging}) + \delta_{eVMT}(\text{Excess Charging}) \\ &= e_{obs} - e_{obs}^{J2841} \end{aligned} \tag{11}$$

Next, I examine the effect of variations between Observed Daily VMT (DVMT) and Reference DVMT distributions. If the DVMT distribution is partitioned into two regions (DVMT less and more than range), charging cannot explain eVMT differences on days when DVMT exceeds the range. This is simply due to the fundamental feature of J2841 UF which assigns the minimum of range and DVMT as eVMT on that travel day and the PHEV is driven in the CS mode only after exhausting the range when DVMT exceeds range. Even if we consider the subset of days when DVMT was lower than the range, it is possible that the difference in eVMT may not be entirely captured by charging alone, i.e. $\left(e_{obs} - e_{ref}\right) \neq \left(e_{obs} - e_{obs}^{J2841}\right)$. This is due to the differences in the DVMT distribution with respect to range. This in turn determines the fraction of range utilized on a given travel day. Therefore, the impact of variations in DVMT distribution can be scrutinized in the form of range utilized or not utilized. I present an intuitive explanation as to why the term $\left(e_{obs}^{J2841} - e_{ref}\right)$ captures the impact of variations in DVMT distributions.

Consider a hypothetical travel day where DVMT is less than range and the Obs DVMT is higher (lower) than the Ref DVMT. According to the J2841 UF, the eVMT estimated using the Obs DVMT is higher (lower) compared to that of the Ref DVMT. Consider the extreme scenario where every day, all the vehicles in Obs and Ref datasets are driven at least their range. The maximum theoretical annual eVMT in this scenario $\left(e_{max}^{J2841}\right)$ based on the J2841 UF assumptions of travel day starting with a fully charged battery every day is $365 \times R_{CD}$. $\left(e_{obs}^{J2841} - e_{ref}\right)$ can be rewritten as shown in Eq. (12) by simply adding and subtracting $\left(e_{max}^{J2841}\right)$ and rearranging the terms.

$$\boldsymbol{\delta_{eVMT}}(\textbf{DVMT distribution and range utilization}) = \left(e_{obs}^{J2841} - e_{ref}\right) = \left(e_{max}^{J2841} - e_{ref}\right) - \left(e_{max}^{J2841} - e_{obs}^{J2841}\right) \tag{12}$$

If $\left(e_{obs}^{J2841} - e_{ref}\right) > 0 \Rightarrow \left(e_{max}^{J2841} - e_{ref}\right) > \left(e_{max}^{J2841} - e_{obs}^{J2841}\right)$ implying that e_{obs}^{J2841} is relatively closer in magnitude to e_{max}^{J2841} compared to e_{ref} resulting in better range utilization by the Obs DVMT distribution. Alternatively, the fraction of range that remains unused by the observed PHEVs is lower than that of the vehicles in the Ref DVMT distribution. This is due to the fact that compared to the NHTS i) Obs DVMT distribution has higher share of days where DVMT was closer to or more than range ; and ii) Average DVMT observed is higher irrespective of whether DVMT was more or less than range . Converse observations are applicable if$\left(e_{obs}^{J2841} - e_{ref}\right) < 0$. By subtracting $\left(e_{max}^{J2841} - e_{ref}\right)$ from $\left(e_{max}^{J2841} - e_{obs}^{J2841}\right)$, I can directly estimate the effect of DVMT variations between Obs and Ref DVMT from Eq. (12). From a distribution perspective, $\left(e_{obs}^{J2841} - e_{ref}\right)$ discerns how range utilized (or not utilized) responds to the separation of distance between the two cumulative distribution function (CDF) of DVMT.

The portion of annual VMT difference that still remains to be accounted for is $\left(g_{obs} - g_{ref}\right) = \left(v_{obs} - v_{ref}\right) - \left(e_{obs} - e_{ref}\right)$. Eq. (10) and Eq. (12) together represent the difference in eVMT between Observed and Reference $\left(e_{obs} - e_{ref}\right)$. This surplus (or deficient) eVMT observed is equivalent to deficient (or surplus) gVMT in the reference travel dataset. Therefore, while examining the impact of variations in annual VMT, only the net gVMT that still has not been accounted for must be considered as shown in Eq. (13). Eq. (13) forces Δ_{gVMT} to be negative in case the variations in eVMT captured by Eq. (10) and Eq. (12) subsumes the variations in total VMT so that in this case gVMT is not treated as excess gVMT observed.

$$\boldsymbol{\delta_{gVMT}}(\textbf{Annual VMT}) = \left|v_{obs} - v_{ref}\right| - \left|e_{obs} - e_{ref}\right| \tag{13}$$

Finally, I address the difference between EPA label and observed range. The label range is determined by testing the PHEV using standardized dynamometer drive cycles [91] in accordance with the recommended practices outlined in J1711. In CD mode, electrical energy consumption is influenced by vehicle driving speed, acceleration, road network topology and prevailing traffic conditions. If the observed PHEVs are driven more aggressively (high speeds/acceleration, higher share of highway specific driving compared to city specific driving for example) compared to the test cycles, their kWh/mile will be higher than the label kWh/mile. By aggregating the kWh consumed and the miles driven in trips where the engine was never turned on (ZE trips), I calculate the kWh/mile consumed. The average usable electrical energy per eVMT when the PHEV is operated in the CD-EV mode (ZE trips) will be used as an indicator to gauge by how much on-road EPA label expected range differ. This quantifies the relative electrical energy efficiency, i.e., the ratio of observed kWh/mile to label kWh/mile or η, Eq. (14). If $\eta > 1$, effective range is lower than label estimates by η. Using this effective range, I recalculate the J2841 UF. The difference between the UF corresponding to effective and label estimates represents the impact of observed driving characteristics deviating from test cycle expectations. It is expressed in UF and as eVMT in Eq. (15)-(16) respectively. Though this approach is an approximation, it nevertheless provides valuable understanding of whether the test cycles adequately reflect real-world operation and on-road energy consumption. Estimating the impact of driving conditions and style on effective range at every operating point or understanding the relationship between kWh/mile and speed or acceleration was deemed out of scope for this study and therefore I use this simplified form.

$$\eta = \frac{\left(\frac{kWh}{mile}\right)_{obs}}{\left(\frac{kWh}{mile}\right)_{ref}} \ \textit{in ZE trips (no engine turn-on event)} \tag{14}$$

$$\boldsymbol{\delta_{UF}}(\textbf{Efficiency}) = UF\left(R_{CDobs} = \frac{R_{CDref}}{\eta}\right) - UF\left(R_{CDref}\right); \tag{15}$$

$$\delta_{eVMT}(\text{Efficiency}) = \delta_{UF}(\text{Efficiency}) \times v_{ref} \tag{16}$$

The left-hand side of Eq. (10), (12) and (13) are divided by v_{ref} and then summed with the left-hand side of Eq. (16). ΔUF is the actual deviation in UF, Eq. (17). ΔUF is expressed as the sum of deviations due to four aspects of driving and charging, Eq. (18). I use $\pm$ to indicate that the contribution to $\boldsymbol{\Delta UF}$ could be positive or negative except for annual VMT since it represents CS mode gVMT. To account for circumstances which the four factors explained above may not entirely capture, an error component to denote the unobservable factors has been included. The authors would like to draw the distinction between this error component from random errors and latent factors which varies from vehicle to vehicle. Error in the context of this methodology accounts for the remaining difference due to unobservable factors, Eq.(19).

$$\boldsymbol{\Delta UF = IUF_{obs} - IUF_{ref}} \tag{17}$$

$$\boldsymbol{\Delta UF \cong \pm\delta_{UF}(\textbf{Charging}) \pm \delta_{UF}(\textbf{Range Utilization}) \pm \delta_{UF}(\textbf{Annual VMT}) \pm \delta_{UF}(\textbf{Efficiency})} \tag{18}$$

$$\boldsymbol{\Delta UF = \pm\delta_{UF}(\textbf{Charging}) \pm \delta_{UF}(\textbf{Range Utilization}) \pm \delta_{UF}(\textbf{Annual VMT}) \pm \delta_{UF}(\textbf{Efficiency}) \pm \delta_{UF}(error)} \tag{19}$$

The individual contribution, $\delta_{UF}(.)$ to $\boldsymbol{\Delta UF}$ is expressed as a percentage of total absolute deviation as shown in Eq.(20). To check the accuracy of the procedure, I calculate IUF estimated by the procedure($IUF_{obs.est}$) according to Eq. (21), compared it with the actual observed IUF ($IUF_{obs.actual}$) and express the percentage error as shown in Eq. (22).

$$\boldsymbol{\delta_{UF}}(.)\,\% = \frac{\delta_{UF}(.)}{|\delta_{UF}(Observed\ Factors)|+|\delta_{UF}(\text{error})|} \tag{20}$$

$$\text{where}|\delta_{UF}(Observed\ Factors)| = |\delta_{UF}(\text{Charging})| + |\delta_{UF}(\text{Range Utilization})| + |\delta_{UF}(\text{Annual VMT})| + |\delta_{UF}(\text{Efficiency})|$$

$$IUF_{est} = \quad IUF_{ref} - \Delta UF \tag{21}$$

$$\%\ Error = \frac{(IUF_{obs.actual} - IUF_{obs.est})}{IUF_{(.)}}\ ; where\ (.) \in \{Ref, Obs, Est\} \tag{22}$$

2.4 Results

In this section, I describe the consequences of implementing the procedure outlined in section 2.3.4 using the driving and charging data collected from the 153 PHEVs. First, I performed tests for statistically significant differences between the UF of observed PHEVs and the SAE J2841 reference estimates. Second, I apply the J2841 UF method on the observed data and discuss the impact of charging. I then investigate how daily VMT distribution influences range utilization. Relationship between annual VMT, charging frequency and UF is analyzed followed by a comparison between observed and label expected range and fuel economy. I synthesize my findings using the functional form represented in Eq. (19)-(22) in the concluding part of this section.

2.4.1 *Tests for statistical significance*

Observed IUF and FUF of all PHEVs except Gen 1 Volt is lower than their respective Reference UF estimates, Table 2.2 and Table 2.3. Though at an aggregate fleet and average vehicle level, there are differences between the Observed UF and Reference J2841 estimates, I want to ascertain if these differences are statistically significant and merit examining in detail. This was accomplished by comparing the UF (sample) of every vehicle in the dataset with the J2841 FUF and J2841 IUF (population) using t-tests and equivalence tests.

I first performed two-tailed one sample t-tests between the UF of every vehicle in the dataset with the J2841 IUF and J2841 FUF. The null hypothesis if rejected indicates that the sample Obs UF value is not equal to the hypothesized population means. At 5% significance level, the null hypothesis test of J2841 IUF was rejected for the Prius, Energi, and Gen2 Volt. Null hypothesis test for the J2841 FUF was rejected for the Prius and Gen1 Volt. I then checked if the Obs UF is within a certain interval around the population means. To perform the equivalence tests, suitable upper and lower equivalence bounds need to be specified based on the smallest effect of interest. The null hypothesis is the existence of a true effect that is at least the chosen lower or upper equivalence bound and the alternative hypothesis is that the effect falls within the chosen equivalence bound or the absence of any worthwhile effect [92]. To determine the effect size, I used standardized differences between the two means, namely Cohen's d and selected the small effect size of 0.2 [93, 94] .

The equivalence bound is the product of *d* and the sample standard deviation. Analysis indicated that the observed IUF and FUF of all the four PHEV models are not equivalent to the J2841 IUF and J2841 FUF at 5% significance level respectively. The results of the t-tests and equivalence tests are summarized in Tables A4-A7 in Appendix A. Using G*power [95], post-hoc effect size and achieved statistical power for the sample size was calculated and summarized in Table A8 in Appendix A. I have included the FUF only as a guide and for the purpose of carrying out the statistical tests. Throughout the reminder the rest of the paper, I consider the multi-day (MDIUF) for analyzing UF discrepancies. Unless otherwise explicitly specified, UF and IUF refer to the MDIUF.

2.4.2 *Effect of charging*

For each of the four PHEV models, I applied the J2841 method on the dataset and generated the UF curves. Figure 2.5 depicts these UF curves alongside the J2841 IUF (solid black line) and J2841 FUF (dashed black line) curves. shows the observed IUF, observed IUF after applying the J2841 UF method, and the reference J2841 IUF.

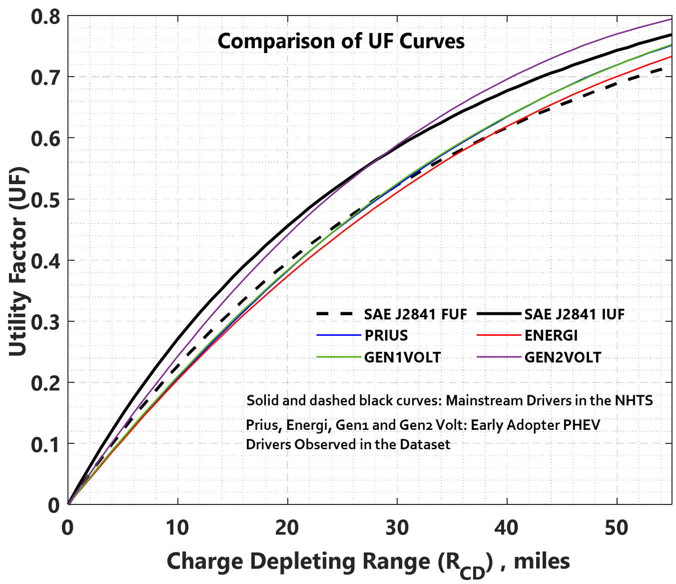


Figure 2.5 Comparison of J2841 UF curves (truncated) generated using NHTS/J2841 estimates and observed PHEVs

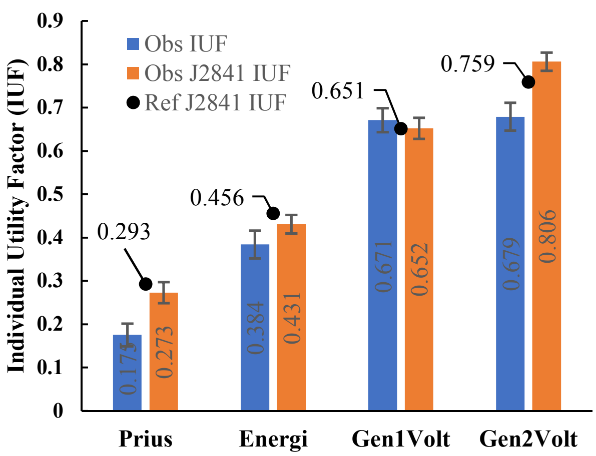


Figure 2.6 Means and std. error of Observed IUF, observed IUF after applying J2841 UF method, and reference J2841 IUF.

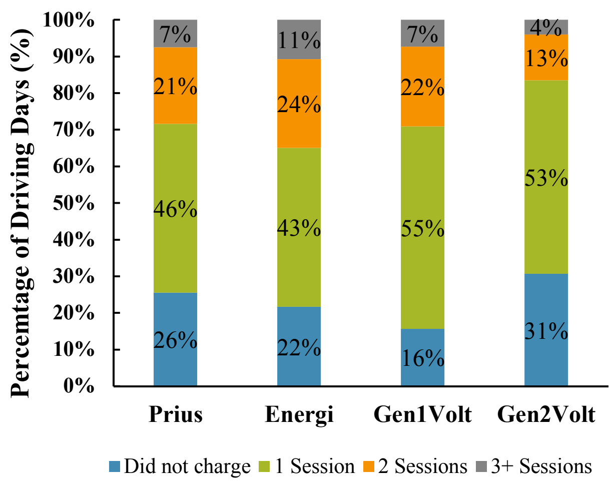


Figure 2.7 Percentage share of driving days by number of charging sessions

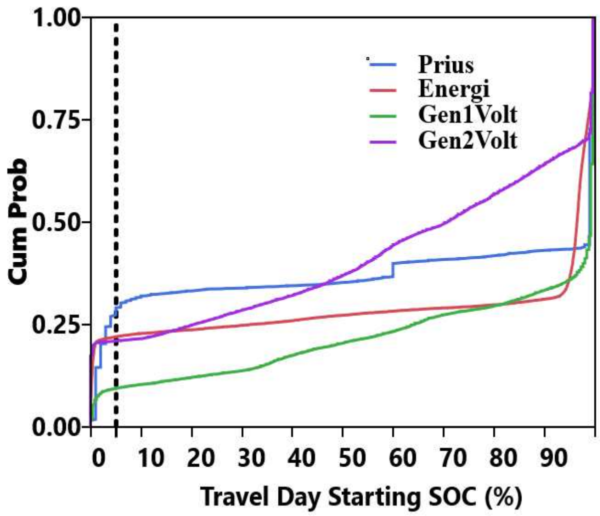


Figure 2.8 CDF plot of travel day starting SOC

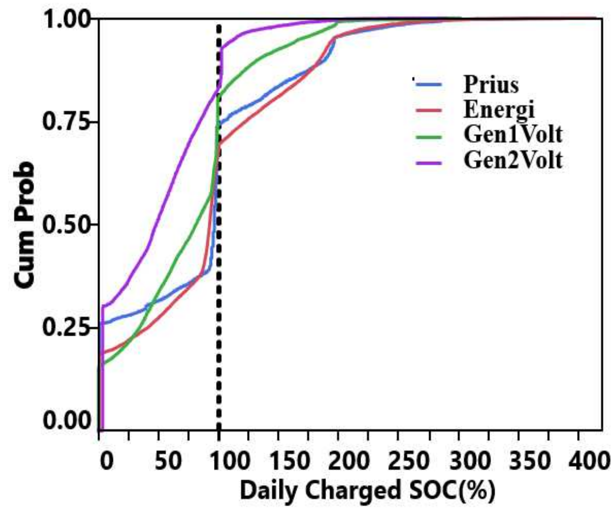


Figure 2.9 CDF plot daily charged SOC

Referring to Figure 2.6, we can see that except for the Gen1 Volt, the IUF increased by varying degrees. The increase in IUF was highest for Gen2Volt followed Prius, and Energi. Figure 2.7 shows the percentage share of driving days by the number of charging sessions. We can see that on roughly 20%-35% of driving days, the PHEVs charged more than once and on 15%-30% of the driving days, the vehicles were not charged at all, both of these situations are not included in the J2841 UF. Referring to Figure 2.8, which shows the CDF of battery SOC at the beginning of travel day, on approximately 25% of driving days Prius and Energi started their travel on nearly empty battery (less than 5% SOC remaining indicated by the vertical dashed line in Figure 2.8), which also contradicts with the J2841 assumptions. The other charging related aspect not captured in J2841 UF is the possibility of PHEVs extending their CD mode of operation beyond their range by charging more than 100% of SOC. Figure 2.9 shows the CDF of daily charged SOC. On approximately 10-30% of days, PHEVs either charged more than 100% or did not charge at all depending on the range.

At a daily level, I calculated the difference between the observed daily eVMT and the expected J2841 eVMT. I analyzed the effect of charging by categorizing the travel day into three types: PHEVs inadequately charging when Daily VMT(DVMT) is less than range; ii) charging when DVMT exceeds range; and iii) PHEVs exceeding their range capability by charging more than 100% SOC. The effect of charging on δeVMT is shown in Figure 2.10 I categorized the travel day into three types to illustrate how charging behavior influences δeVMT with respect to range. Gen1 Volts overcompensates for the eVMT missed due to not charging adequately by regaining eVMT beyond their range by charging more than 100% of SOC.

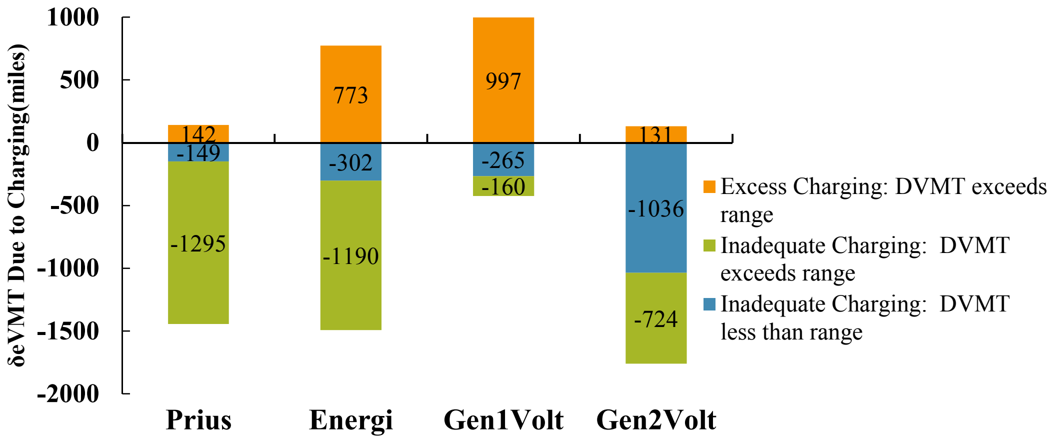


Figure 2.10 Effect of charging on average annualized δeVMT

The effect of charging is most pronounced in the case of short-range PHEVs (Prius and Energi) followed by Gen2 Volts. The eVMT missed due to inadequate charging and eVMT gained by charging more frequently by Gen2 Volt reduced appreciably compared to Gen1 Volt.

Table 2.5 Kolmogorov-Smirnov Two-Sample Test Report[$]

	KS test statistic	**D = Max|F1-F2|**	**Observed CDF at D**	**NHTS CDF at D**	**Observed DVMT at D**	**Prob >D**
Prius	0.058	0.152	0.264	0.416	20	<.0001*
Energi	0.0638	0.137	0.429	0.567	30	<.0001*
Gen1Volt	0.056	0.125	0.389	0.508	26	<.0001*
Gen2Volt	0.043	0.099	0.203	0.303	14	<.0001*

**Statistically significant at 5%. p <.0001* rejects null hypothesis that the two samples were drawn from the same distribution. [$]Table A10 in Appendix A presents additional details including the test report for the two alternative one-sided hypothesis tests*

2.4.3 Daily VMT distribution's influence on range utilization

Variations in DVMT distribution between analyzed data and NHTS expectations corresponds to variations in range utilization. Additional descriptive details of the distributions are summarized in Table A9 of Appendix A. To examine this further, I compared the CDF of DVMT of observed PHEVs with the NHTS using the two-sample Kolmogorov-Smironov (KS) test. The KS test report is presented in Table A10 of Appendix A. The KS test statistic D measures the maximum absolute deviation between the two CDFs. Of interest is the DVMT at which maximum deviation between the NHTS and observed PHEV CDF occurs in relation to the range.

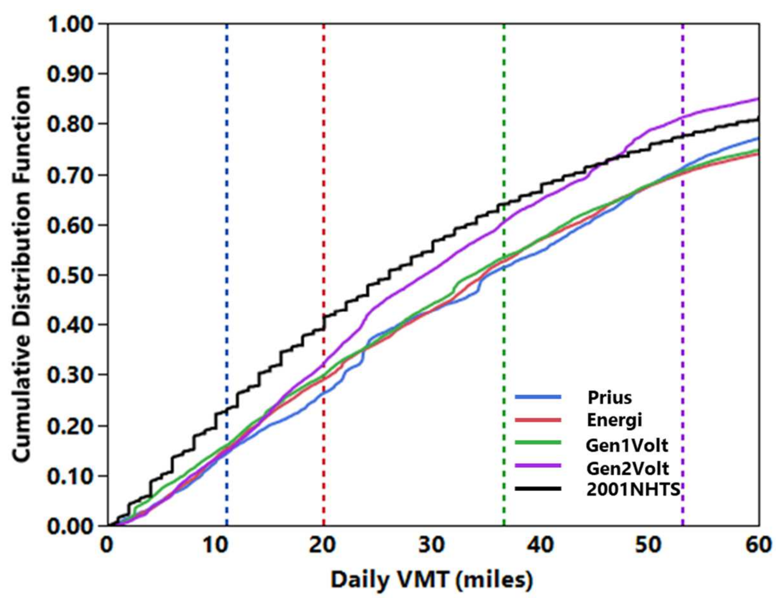


Figure 2.11 Comparison of daily VMT CDF (truncated) between NHTS and observed PHEVs

Referring to Table 2.5, the observed DVMT at which maximum deviation (D) increases with range (up to Gen1 Volt) and then reduces. The maximum deviation for Gen1 and Gen2 Volts happens when DVMT is lower than their range –26 miles and 14 miles respectively. In the case of Prius and Energi, D occurs at a value of DVMT that is 10 miles more than their range. For the Prius and Energi, the D statistic indicates that the observed PHEVs have a higher share of DVMT beyond their range. This is most noticeable for the Prius as evidenced by the value of NHTS CDF (0.416) and observed CDF at D (0.264), which is near the first quartile. For the Energi and Gen1 Volt this occurs closer to the median and in the case of Gen2 Volt, it is below the first quartile.

From Table A9, we can see that the 10%, 25%, 50%, 75%, 90% quantile DVMT of NHTS is lower than those of the observed PHEVs, except for the 75% and 90% quantile DVMT of Gen2 Volt. The mean is higher than the median across all PHEV, indicative of the left-skewed nature of the distributions. However, their extent of separation displays a gradually decreasing trend with increasing range demonstrating that the left-tail of observed PHEVs being much longer than NHTS. This effect is measured using the expression in Eq. (12). Referring to Figure 2.11 , the CDF of NHTS lies entirely above the CDF up to approximately 45 miles. We can observe that the J2841 UF based on the NHTS, under-represents the number of days, DVMT was higher than the range of all PHEVs except Gen2 Volt. In the case of Gen2 Volt, the NHTS over-represents share of days beginning approximately 10 miles below its range. This explains why the IUF of Gen2 Volt increased the most compared to the other PHEVs when the J2841 UF method was applied, Fig. (5). Expanded cumulative distribution and probability density function plots of DVMT are depicted in Figures A1-A2 respectively in Appendix A.

2.4.4 Interactions between annual VMT, charging sessions and IUF

Calculating the net gVMT portion of annual VMT variation between observed and NHTS due to differences in range utilization or charging behavior, is a straightforward task, Eq. (13). I examine the relationships between annual VMT, UF, eVMT, and charging. Table 2.6 summarizes the average annualized VMT, eVMT and UF of the observed PHEVs grouped based on whether Observed annual VMT was more (or less) than Reference annual VMT (15,000 miles). Overall, 48% of observed PHEVs (74 out of 153) drove longer than 15,000 VMT. Approximately 60% of Prius, 54% of Energi, 51% of Gen1 Volt, and 31% of Gen2 Volt drove more than 15,000 miles annually. Referring to Table 2.6, I can see that UF reduces as the total VMT increases, since the UF is a ratio of eVMT to total VMT. If we look at ΔeVMT of Prius and Gen2 Volt that drove less than Reference annual VMT (15,000), their observed IUF was still less than the J2841 IUF.

Table 2.6 Relationship between average annualized VMT, charging sessions, UF and eVMT

	N Vehicles		**VMT**		**eVMT**		**gVMT**	
	Below 15000	Above 15000	Below 15000	Above 15000	Below 15000	Above 15000	Below 15000	Above 15000
Prius	9	13	9597	21165	2444	2483	7153	18682
Energi	24	28	11204	21422	5232	5831	5972	15591
Gen1Volt	21	22	10727	21107	8236	12218	2491	8890
Gen2Volt	25	11	12052	18806	8338	12050	3714	6756
	Observed IUF		**Reference IUF**		**Charging Sessions/DrivingDay**		**ΔeVMT (Obs-Ref)**	
	Below 15000	Above 15000	Below 15000	Above 15000	Below 15000	Above 15000	Below 15000	Above 15000
Prius	0.255	0.117	0.293		1.47	1.24	-1951	-1912
Energi	0.467	0.272	0.456		1.69	1.69	-1608	-1009
Gen1 Volt	0.768	0.579	0.648		1.47	1.69	-1484	2497
Gen2 Volt	0.692	0.641	0.759		1.06	1.28	-3047	665

Increase in the annual VMT traveled is associated with increase in charging frequency of all PHEVs except the Prius and Energi. Table 2.6 shows that the IUF of Gen1 Volt being slightly more than the J2841 UF is stemming from the group that drove more than 15,000 miles. In the case of Gen1 Volt, though charging contributes to IUF slightly exceeding J2841 IUF, the effect of range utilization also plays an equally important role. Referring to Figure 10 , the additional eVMT beyond its range gained by Gen1 Volt was the highest , followed by the Energi, Prius, and Gen2 Volt. On an absolute eVMT basis, Gen2 Volt missed more eVMT by charging inadequately on days when the daily VMT was less than its range compared to the eVMT missed on days when daily VMT exceeded its range. than all other PHEV models (Figure 2.10). If we consider ΔeVMT of short-range PHEVs (Prius and Energi), it is worthwhile to note lower annual VMT was associated with slightly higher (Prius) or relatively comparable (Energi) frequency of charging when compared to the group that drove more than 15,000 miles annually.

The average annual VMT across the entire dataset of 153 PHEVs is 7% more (15,868 miles) than the EPA label reference 15,000 miles. I selected 15000 miles as the cut-off based on the EPA fuel economy label assumption[67] but in general annual mileage depends on a variety of aspects such as built environment characteristics (land-use mix, sprawl, housing and population densities) [96], socio-demographic attributes, typical travel needs [97], rebound effects [98], and charging accessibility[99]. In this study, the short-range PHEVs (Prius and Energi) have higher annual mileage than the longer-range PHEVs (Gen1 and Gen 2 Volts). From a directional perspective, this observed trend is consistent with evidence from nationwide studies in which the average annual VMT was estimated to be 12,400 miles , up to 20% lower than short-range PHEVs[86, 100]. Annual VMT comparisons between this study and other PHEV observational studies are summarized in Table A13 of

Appendix *A*.

To further understand annual mileage differences between short-range and longer-range PHEVs, I compared the frequency (days/year) of long-distance travel (daily VMT 50 miles or more) and charging accessibility as they are reasonable indicators of annual mileage and IUF deviations[99, 101, 102]. Prius, Energi, and Gen1 Volt had a comparable number of long-distance travel days (115 days/year), whereas Gen2 Volts were used for long-distance travel only on 78 days/year on average. Contribution of long-distance travel (100 miles or more) to annual mileage of Prius and Energi exceeded the Gen1 Volt and Gen2 Volt by roughly 3% and 6% respectively. These are depicted in Figures A4 and A5 of Appendix A.

The online survey asks the respondents to specific over the past 30 days whether they charged at their home only or away from home only or both at home and away locations. I used this categorical variable for the purpose of examining the impact of charging accessibility on annual mileage and IUF. Figure A6 depicts the mean and standard error bars of annual VMT and IUF grouped by PHEV type (Prius, Energi, Gen1 Volt, Gen2 Volt) and charging accessibility (Home, Away, Home and Away). Overall, we find that PHEVs that charged at *home* on average have higher annual VMT compared to the sub-group that charged at *away* locations and this holds true for the IUF as well (except in the case of

Prius). My analysis indicated that Energi and Volts (Gen1 and Gen2) that charged at *home and away* locations have the highest UF and annual VMT among their respective sub-groups. We can also observe that short-range PHEVs (Prius and Energi) that charged at home and away locations on average have comparable annual mileage (17,000 miles) and the highest across the 12 groups (four PHEV types and three categories of charging accessibility).

2.4.5 Impact of ZE trip efficiency on effective range

In order to assess how efficiency of the ZE trips (kWh/mile) influences the effective range on road, I compare the results to three EPA dynamometer drive cycles that are integral to many of the performance and fuel economy standards: Urban Dynamometer Driving Schedule (UDDS), Highway Fuel Economy Test (HWFET) and Supplemental Federal Test Procedure (FTP) or US06. I express efficiency as the ratio of per-mile electrical energy consumption in ZE trips (trips where engine was never turned on) observed to the EPA label rated values. Considering the powertrain design of the Volt, which enables it to be driven as a BEV up to its range [103], and for the purpose of not penalizing the short range PHEVs unfavorably due to their smaller range and blended mode of operation, I consider the efficiency of ZE trips alone. This is in consistent with California's test procedures which measures the electrical energy consumed in CD-EV mode[104].

UDDS and HWFET are intended to characterize typical urban and highway driving styles respectively. The US06 finds its specific application to capture engine turn-on events under high speed and aggressive acceleration as part of determining the ZEV credit under California's ZEV mandate. Figure 2.12 (a) shows the percentage share of VMT comparison between the commonly used test cycles for fuel economy and range measurements alongside the entire fleet of PHEVs observed and NHTS by speed in mph. For the test cycles and the observed PHEVs, the distances were grouped binned based on the actual distance driven in 5mph speed bin intervals. For the NHTS, I used the average trip speed to bin the trip distances. Figure 2.12 (b) compares the share of travel at different speeds between the PHEVs observed.

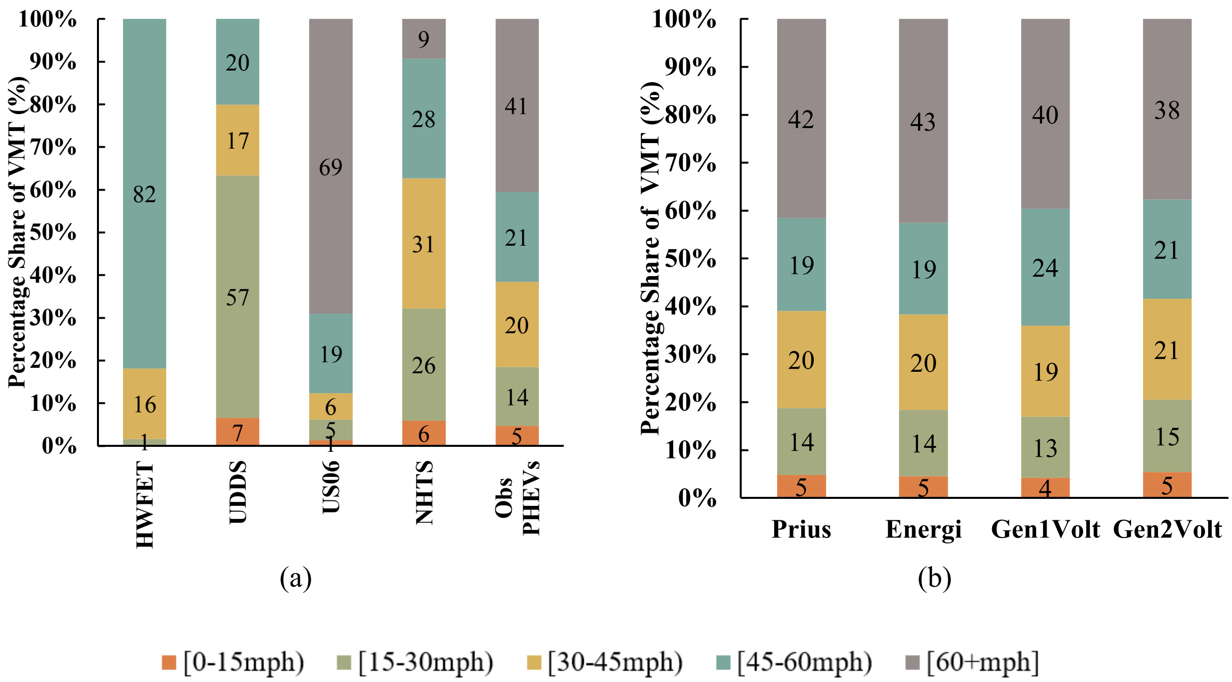


Figure 2.12 (a): Percentage share of VMT comparison between test cycles, observed PHEVs and NHTS by speed bins; (b): Percentage share of VMT comparison by speed bins

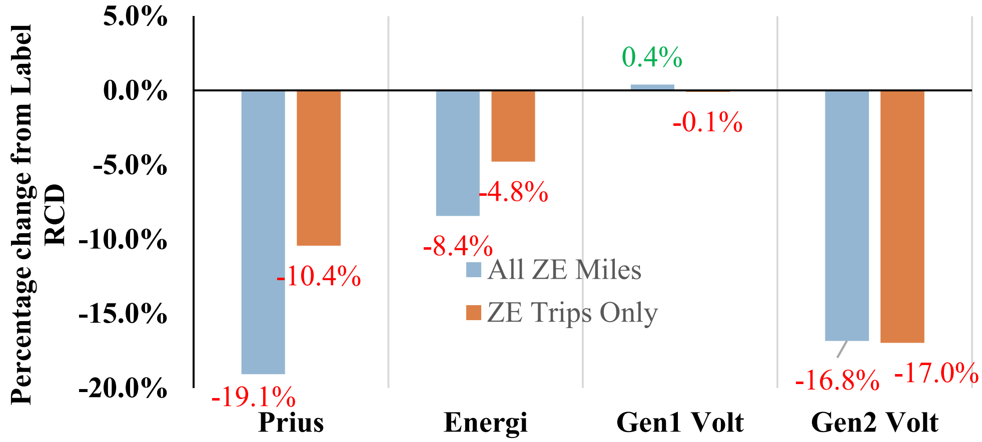


Figure 2.13 Percentage difference between effective and label range

Overall, we can see that there are noteworthy differences between the test cycles and observed PHEVs, especially high speed (60+ mph) travel which neither the UDDS nor HWFET capture. If we use the average trip speed as a classifier to compare driving characteristics of NHTS vehicles with observed PHEVs, high speed travel (60+mph) is under-represented by roughly 30%. Figure 2.12 (b) illustrates that even among the PHEVs, there are differences in share of VMT above 45mph. The Volts accomplish a higher share of VMT at 45-60 mph but a lower share of VMT at 60+ mph compared to the Prius and Energi. If we use 45mph as cutoff to classify city driving (J2841 UF uses 42mph as the threshold to obtain 55/45 city and highway driving split on the NHTS data), the city/highway driving split observed is almost 40/60. Figure 2.13 shows the effective range calculated. For the sake of completeness I present the effective range when we consider only the ZE trips (trips where the engine did not turn) and ZE miles which includes the ZE trips and fraction of eVMT in the blended mode of operation before the first engine turn-on event. The effective range based on the energy consumption of ZE trips on average can be as low as only 83% (Gen2 Volt) of the label range or slightly more than label range (Gen1Volt).

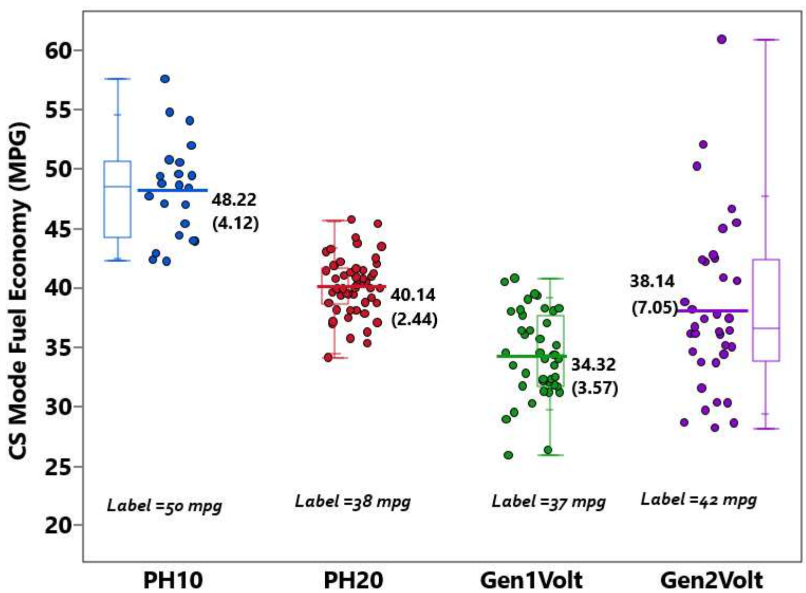


Figure 2.14 Distribution of observed PHEV charge sustaining mode fuel economy (mpg). Standard deviation shown within parentheses below the mean values and label values shown inset.

If the actual range realized on-road is less than the label expected range, the vehicle enters the CS mode after driving relatively shorter distances compared to test cycle expectations. Furthermore, due to the underrepresentation of high-speed travel in the test cycles compared to the observed share of VMT by driving speeds (Figure 2.12)when considered in conjunction with the observed PHEVs not realizing the label expected range on-road (Figure 2.13), has direct implications on the fuel economy in CS mode. Figure 2.14 shows the distribution of observed CS mode fuel economy. On average observed CS mode fuel economy (mpg) differed from label values on average by -9% to +6%.

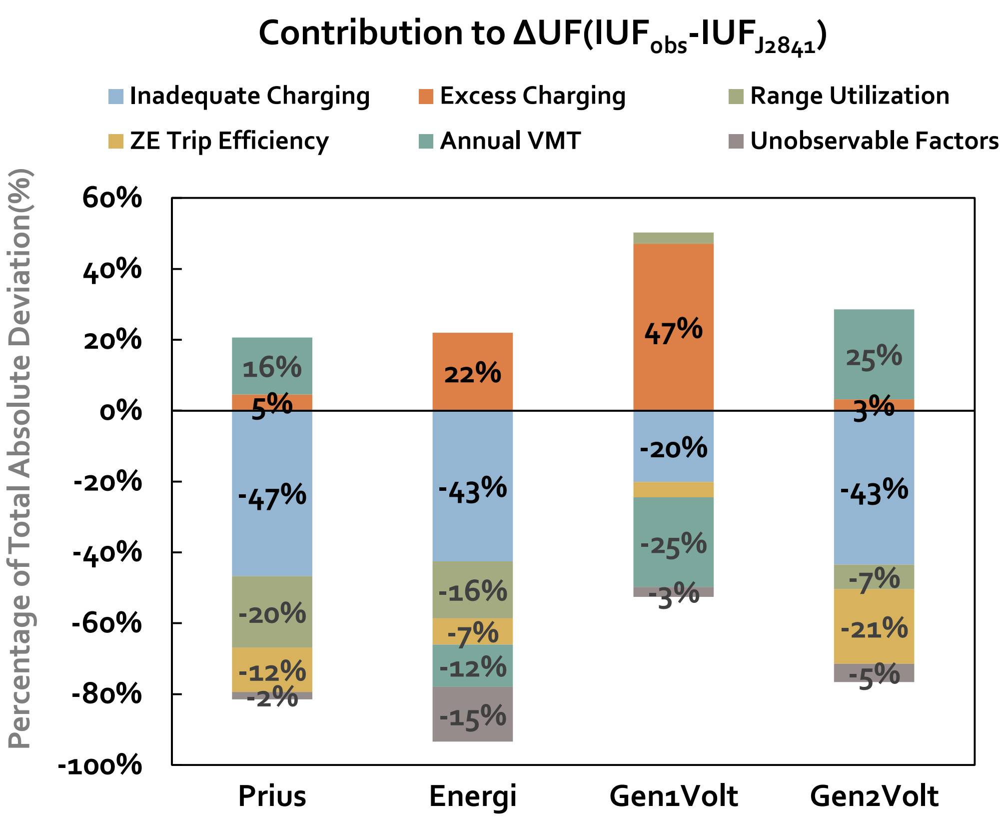


Figure 2.15. Combining the effect of charging behavior, range utilization, ZE trip efficiency, and annual VMT. Individual contribution is expressed as percentage of total absolute deviation, Eq. (19)-(20). Percentages shown are average and the standard errors are presented in Table 2.7.

Table 2.7 Distribution of the contribution to IUF deviations. Mean and standard error

	Inadequate Charging	**Excess Charging**	**Range Utilization**	**ZE Trip Efficiency**	**Annual VMT**
Prius	-46.6% *±6.7%*	4.6% *±2.3%*	-20.2% *±1.6%*	-12.5% *±8.6%*	16.0% *±15.1%*
Energi	-42.5% *±6.4%*	22.0% *±5.3%*	-16.1% *±3.1%*	-7.4% *±9.0%*	-11.9% *±13.6%*
Gen1Volt	-20.1% *±8.5%*	47.1% *±13.7%*	3.2% *±15.7%*	-4.4% *±4.3%*	-25.2% *±28.9%*
Gen2Volt	-43.4% *±8.5%*	3.2% *±2.0%*	-7.0% *±11.2%*	-21.0% *±6.7%*	25.4% *±13.3%*
Values are Means ± *standard errors in italics*					

2.4.6 Consolidated effect of all observed variations

The individual effect of the four key driving and charging aspects are aggregated and depicted in Figure 15. The functional relationships between the observed IUF and the sources that contributed to its deviations from J2841 IUF were described in Section 2.3.4. The effect of charging, range utilization, annual VMT, ZE trip efficiency, and unobservable factors are expressed as percentage of total absolute deviation, Eq. (17) – Eq. (20) . The effect of charging is broken down into inadequate charging on both types of travel days (DVMT more and DVMT less than range) and excess charging on days when driving more than the range as explained in Section 2.4.2. With the inclusion of an error component to capture the unobservable factors, the absolute value of the percentages shown in Figure 15 will sum to 100%. For clarity, the mean along with the standard errors are summarized in Table 2.7.

The net impact of charging is the dominant cause of Prius and Energi IUF being lower than J2841 IUF expectations even though both on average charge more than once per day. On roughly 20-30% of days, Prius and Energi started their travel day on a nearly empty battery, and this is clearly illustrated in Figure 2.8. The second major reason is the influence of DVMT distribution on range utilization. This is mainly due to NHTS underrepresenting the share of travel accomplished on days when the Prius and Energi drove longer than their respective range. The negative impact of ZE trip mile efficiency (observed kWh/mile higher than EPA label rated kWh/mile) on Prius was slightly more compared to Energi. Despite Prius driving 1432 miles more than the reference annual VMT (15,000 miles), variations in charging and range utilization together accounted for 1928 miles of missed eVMT. In the case of Energi, there is still a portion (419 miles), of annual VMT not captured by variations in charging and range utilization. Consequently, the effect of annual VMT on Prius and Energi are displayed as positive and negative respectively, Figure 2.15.

There was considerable difference in the relative contribution of the four key driving and charging aspects towards the IUF deviations from label values between the Gen1 and Gen2 Volts. Average daily charging frequency of Gen1 Volt was the highest and its IUF was slightly higher than the J2841 UF expectations. This is mainly due to the negative impact of higher annual VMT (1,000 miles more than the reference annual mileage of 15,000) being almost entirely offset by the positive impact of charging more frequently. Furthermore, it is also aided in part by better range utilization and slightly better ZE trip mile efficiency. Among all PHEVs and especially within the Volts, a symbolic feature of Gen1 Volts observed is their effectiveness in coordinating travel needs with charging behavior. The Gen2 Volt had the lowest annual VMT, lowest charging frequency/day and highest share of days on which it did not charge, Figure 2.7. The positive impact of lower annual driving was dominated by the negative effects of not charging adequately and kWh/mile of ZE trips being more than the label estimated values.

Observed charging behavior differing from the baseline single charge session per day and the travel day starts with a fully charged battery alone contributed to IUF deviating from label values of Prius and Gen2 Volts by -40% (Prius and Gen2 Volt), -21% in the case of Energi , and +27% in the case of Gen1 Volt. Differences in range utilization between NHTS and observed was responsible for -20% to +3% of IUF deviation from J2841. Differences in annual VMT accounted for ±25% of deviation in observed IUF from J2841 UF. Observed PHEVs accomplish a higher share of VMT at speeds (45mph or more) that is not captured by EPA certification cycles or the NHTS. Therefore, effective range of observed PHEVs realized on-road was lower than EPA label range. Variations between effective range and EPA label range influenced the IUF deviation by -20% to +1%.

Figure 2.16 shows the observed IUF actual , observed IUF estimated by subtracting the deviations explained by Eq.(19) in Section 2.3.4 from the reference J2841 IUF $\left(IUF_{est.} = IUF_{ref} - \Delta UF\right)$, and the reference J2841 IUF. I calculated difference between the actual observed and estimated IUF. If we express this difference as a percentage of the of the observed IUF (actual) , the procedure outlined in this chapter underestimates the observed IUF (actual) of Prius by 2%, Energy by 15%, Gen1 Volt by 3 %, and Gen2 Volt by 5%.

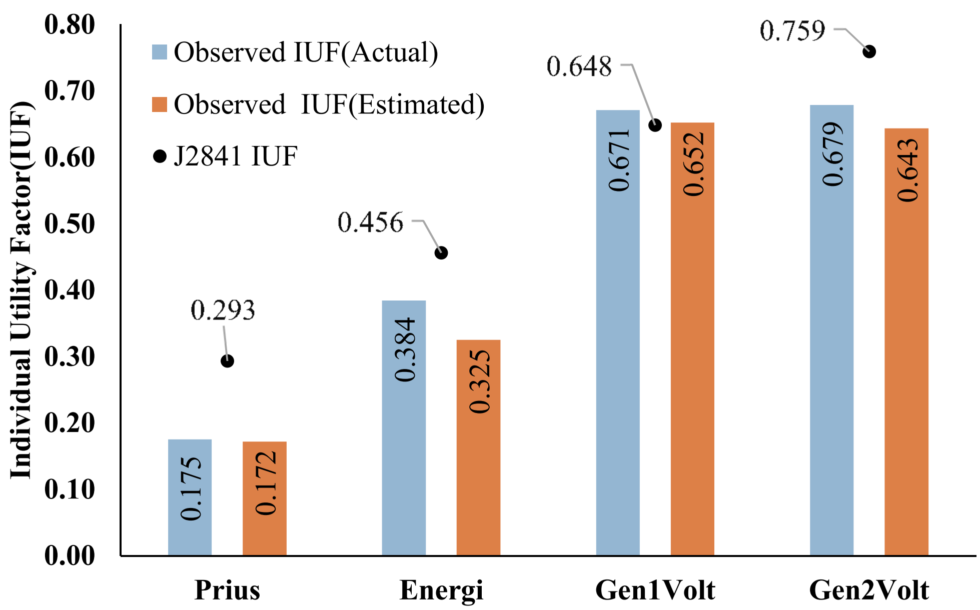


Figure 2.16. Comparison of actual IUF and IUF estimated alongside the reference J2841 IUF. Observed IUF are vehicle weighed average of UF by definition of IUF. Estimated and observed IUF are average values.

2.5 Discussion

Electrification of LDVs is essential to reduce gasoline consumption and emissions in the U.S. In this regard, PHEVs continue to receive attention as an attractive vehicle technology option in the transition towards complete electrification. Utility Factor (UF), which denotes the fraction of travel electrified, is used to measure the performance of PHEVs and is formally defined in the SAE J2841 standard. I used year-long driving and charging data of 153 PHEVs (22 Toyota Prius, 52 Ford CMax/Fusion Energi, 43 Gen 1 Volt and 36 Gen2 Volts) with 11-53 miles of range from California, and systematically evaluated how their real-world operation deviates from the J2841 assumptions. I then quantified how each of these deviations contribute to the observed UF of PHEVs varying from their respective J2841 estimates. I elaborated on the salient traits of PHEVs observed that are not sufficiently addressed or entirely excluded from the J2841 framework in its current form.

Three charging aspects were observed that markedly differed from the J2841 UF charging assumptions of a single charging event per day and the travel day stating with a fully charged battery: i) the tendency of PHEVs, especially those with short range (Prius and Energi) to start their travel day on an empty battery and be driven as a regular HEV; ii) PHEVs charging on average more than once per day (except Gen2 Volt) and on roughly 15-35% of days, PHEVs charged more than twice per day depending on the range and as a consequence iii) possibility for PHEVs to fully recover or even exceed their range by charging more than 100% of their SOC. This brings up an important feature missing in J2841, impact of additional charging beyond once per day on eVMT and UF and broadly speaking the value of public charging infrastructure on PHEV adoption and utilization[105]. Though my analysis indicates that the short-range PHEVs (Prius, Energi) and Gen2 Volt missed eVMT due to not charging adequately, it could be due to contrasting reasons. In the case of short-range PHEVs, lack of sufficient incentive maximize eVMT due to short-range, self-selction bias by users who are less likely to charge or their purchase motivation was other incentives like upfront rebate, HOV lane access, and preferential parking spaces

[106]. In contrast, Gen2 Volt not charging could be due to their higher range capabilities coupled with the fact that their average DVMT (39 miles) was the lowest among all the PHEVs analyzed in this chapter.

Prius, Energi, and Gen2 Volt are presumed to electrify a higher share of VMT according to the J2841 UF estimates compared to what they accomplished in the California sample of 153 PHEVs analyzed in this study. The characteristics (average, quantile, median, share of travel below their range, skewness, and kurtosis) of daily VMT distribution observed varied noticeably from the NHTS. When combined with the basic feature of J2841 UF which assumes that the PHEV switches to the CS mode only when daily VMT exceeds range, induced diverse impacts on IUF. Gen1 Volt had a slightly higher annual VMT, charged more on average, and has a higher IUF than the Gen2 Volt. Even though Gen2 Volt has a bigger battery and longer range, its IUF and annual eVMT was lower than that of Volt38. Moreover, the average daily VMT of Gen2 Volt (39 miles) was below its range. This could be to the misalignment between user's driving needs and the range either and/or there were other factors in play such as desire for the occasional long trips without having to charge. Marginal increase in battery capacity did improve IUF and absolute eVMT in this dataset, except in the case of Gen2 Volt.

The J2841 method presumes that all consumers utilize range equally and the marginal benefits of increasing the range is realized by all consumers in a homogenous manner. Moreover, this assumption dilutes the perception and adoption of PHEVs with varying range and drivetrain topologies in different market segments[107]. This suggests that irrespective of sociodemographic indicators, potential PHEV owners, are indifferent to range– meaning that their travel demand has no bearing on the range of the PHEV they eventually purchase. The NHTS draws its sample from mainstream ICE owners. Assuming travel patterns of PHEVs are identical to ICEs irrespective of range presents an incomplete and uncertain picture of how different consumers value and utilize the same range. There is notable variation in UF for the same range (Figure 2.3), indicative of the fact that not all users value and utilize range homogenously. This is in stark contrast to the assumption in J2841 that users are indifferent to range which effectively decouples travel demand of potential PHEV users from the range of PHEV they eventually decide to buy.

The net environmental benefits of PHEVs depend on eVMT, which hinges on the ability of PHEVs to fully utilize their range. However, the effective range realized on the road depends on driving style (city dominant or highway dominant for example), ambient conditions, traffic, and road network topology. Analysis indicated that the effective range realized on road was lower than the EPA label estimates for all four PHEV types. This could potentially be due to certification cycles underestimating travel at high speeds. In the medium to long-term if the trend towards high speed travel persists, it will adversely impact their life-cycle environmental and value proposition calculations. The share of VMT at 60+mph by the short-range PHEVs (Prius and Energi) was higher than that of the Volts, where the share of travel at 45 mph-60 mph by the Volts were higher than that of the short-range PHEVs. EPA test cycles (UDDS and HWFET) and the J2841 method of trip allocation do not reflect the city/highway style driving observed across all the four PHEV types. The J2841 UF and the EPA CD test procedures are ultimately built on the hypothesis that daily VMT encapsulated in the NHTS is just a gradual extension of driving styles represented by the test cycles for range measurement [39, 108].

A fundamental issue in evaluating the performance of PHEVs is understanding the context and experimental design under which the data was collected to estimate the UF. This is important for three reasons. First, results presented in this study clearly demonstrated that the observed PHEVs and J2841 charging and driving assumptions vary across trip, daily, and annualized timescales. It is difficult to interpret the actual performance of PHEVs calculated from data sources that are neither comparable nor compatible from a vehicle technology, time-scale, or target respondent perspectives. Secondly, in the case of studies that report UF from actual PHEVs, though technological capabilities are geographically neutral, however ambient conditions, road network topology, travel demand and user behavior are not. California is considered as a leader in the U.S. for implementing policies to mitigate the adversarial impacts of climate change concerns and has a plethora of policies that encourage PEV adoption. The performance of PHEVs observed in this analyses will be markedly different from elsewhere. Finally, apart from regional differences, as this study indicated, travel demand and charging behavior varied with range. To ensure consistency in the comparative assessment of UF with J2841 and also among the observed PHEVs, standardizing with J2841 is critical. I developed a procedure to precisely fill this need.

2.5.1 PHEV Policy and performance implications

The relevance of this article from demand (PHEV users) and supply (OEMs) sides, and regulatory design perspectives are described below. The paper concludes with few remarks on the course of action currently being explored globally which could augment the environmental benefits of PHEVs.

The positive association between demand side purchase incentives, tax exemptions, and registration waivers, and PHEV uptake is well established across many countries. However, increasing efforts have been undertaken to ensure that they are better targeted. Currently the purchase incentives for PHEVs in California irrespective of the range (eligible PHEV models must have at least 10-mile range) is fixed at $1,500. Such a mechanism does not appropriately reward longer-range PHEVs (35-miles or more) even though they have a higher UF and gasoline displacement potential than short-range PHEVs. Furthermore, behavioral aspects particularly charging accessibility and utilization is overlooked. This is also the case in the J2841 methodology which assumes every PHEV is charged once overnight at home and travel day starts with a fully charged battery. By extension, we can posit that the impact of intra-day charging at public charging stations and workplace on the eVMT created is ignored. This could potentially lead to perverse effects being generated in the form of missed eVMT due to not charging and used as a regular HEV, self-selection bias by users who are less likely to charge buying short-range PHEVs, or purchase was motivated by access to car-pool lanes[36]. In The Netherlands and the U.K. ,PHEVs are widely purchased as company cars for which the users get paid for fuel but not electricity is a practical example of a wrongly targeted demand side incentive that by design rewards perverse behavior [109].

One of the globally adopted strategy to promote electrified vehicles (EVs and PHEVs) is to integrate them within corporate average fuel economy and consumption standards through super credits or production multipliers and zero emission accounting provisions for the proportion of grid-electricity enabled operation [110-113]. The UF and thereby the assumptions on charging behavior, representative driving patterns, and test cycles for range estimation are intricately linked to the broader fuel economy standards. Deviations between on-road and label UF directly influences the gap between on-road and test cycle fuel consumption of PHEVs. Observed driving and charging behavior varying from the reference and test cycles not adequately representing real-world driving patterns highlight the need for incorporating realistic driving and charging scenarios for estimating the UF. Withdrawal of several PHEV models from the market in the EU due to non-compliance under the WLTP [114] ; taking advantage of the credit multiplier and zero emissions accounting loophole that rewards short-range PHEVs in fleet fuel consumption standards by treating PHEVs as merely "compliance cars" in the U.S. and EU[115]; and China's proposed fuel economy standards that requires PHEVs to have a minimum range of 31 miles (50 km) credit qualification [116] are few examples that demonstrate how regulatory mechanism and compliance flexibilities influence PHEV supply.

Looking ahead, we can foresee four major developments that could influence the performance of PHEVs from the vantage point of eVMT and UF:

- *Incorporating realistic driving and charging behavior*- 25% reduction in range under WLTP compared to NEDC is a tangible example that illustrates the consequences of adopting realistic test cycles for range measurement. To date no such measure has been considered to account for charging behavior deviating from the single charging session overnight at home and travel day starting on a fully charged battery. Generating UF curves by vehicle class (from compact to SUVs), annual mileage, access to charging, and recharging frequency are potential variants to consider for future PHEV UF assessments.
- *Expanding OBD-II compliance requirements* - Push towards remote monitoring and reporting of important in-use parameters would prevent tampering and increase the effectiveness of inspection and maintenance programs[117]. California's OBD-II

regulations require reporting of blended mode and pure-EV mode eVMT and grid energy consumed, and fuel consumption in the CS mode[118]. Though out of scope of this study, better understanding of PHEV engine-on events and cold-start emissions is of topical interest and one can expect an increase in such efforts –for example Real-world Driving Emissions (RDE) test to complement SAEJ1711/WLTP to accurately measure criteria pollution using Portable Emissions Measuring Systems[119].

- *OEM trends and strategies* – OEMs are gradually shifting towards electrifying larger foot-print vehicles by offering PHEV versions of SUVs with bigger batteries resonating with the growing number of consumers favoring SUVs over passenger cars, especially in the U.S. Prospects for leveraging advancements in Information and Communication Technologies (ICT) through blockchain technology and geofencing capabilities are expected to improve. This serves multiple purposes from mitigating privacy and data security concerns, to accurately monitoring on-road emissions and tracking green miles traveled. This is currently being piloted in Cologne, Germany using a test fleet of 10 PHEVs[120]. A related innovation in design is equipping the PHEVs that would automatically operate in the CD mode upon entering a low or zero-emission zone, such as the eDrive Zone project in Rotterdam, Netherlands[121].
- *Public charging infrastructure expansion* - As the share of potential PHEV owners living in apartment complexes, especially as the uptake of PHEVs increase in dense urban metros, public charging infrastructure would play a crucial role in supplementing home-charging infrastructure or lack thereof.

J2841 UF is widely used to evaluate the performance of PHEVs despite its simplistic and restrictive assumptions about how PHEVs are driven and charged. These assumptions determine how PHEVs are assessed in regulatory and incentive-based policies. The extent to which these assumptions capture real-world operation of PHEVs has a cascading effect on policy signals that inform automakers about future vehicle designs which in turn influences consumer expectations and purchase decisions.

Favorable policies accompanied by improvements in battery technology and powertrain architecture, and charging infrastructure expansion, will increase the number of PHEV model offerings for prospective PHEV users. Consequently, it will be valuable to consider real-world scenarios that deviate from J2841 expectations to enhance the representativeness of UF estimates. As a step in this direction, this study examined PHEV usage and presented insights on their real-world usage.

3 Impact of User Preferences on Plug-In Hybrid Electric Vehicle Utility Factors

3.1 Background

Climate change, air quality, and public health concerns have necessitated that governments across the world implement policies to promote battery electric (BEVs) and plug-in hybrid electric vehicles (PHEVs), collectively addressed as plug-in electric vehicles (PEVs). In the U.S., the transportation sector is responsible for 30% of total national greenhouse gas (GHG) emissions, and the light duty vehicle (LDV) segment alone contributed close to 60% of total transport GHGs in 2017 [1]. In the state of California, 40% of total GHGs comes from the transportation sector, and the contribution from the LDV segment was close to 70% of transport GHGs [2]. California and many other governments have implemented a suite of technology forcing mandates, performance standards for transportation fuels, GHG emissions, and incentive-based policies to increase the market penetration of PEVs [3–5].

Plug-in hybrid electric vehicles are often considered to be a transitional technology with the potential to expedite the shift towards BEVs [6,7]. Plug-in hybrid electric vehicles are equipped with a larger battery pack compared to conventional hybrid vehicles (HEVs) that can be charged using grid electricity, and have an internal combustion engine (ICE). PHEVs are not limited by the range anxiety and higher upfront purchase cost concerns associated with BEVs, and they combine the pure electric driving capabilities of a BEV with the fuel and energy efficiency enhancements due to engine downsizing, low or no engine idling, and regenerative braking capabilities of an HEV. This design and operational flexibility allow them to be driven in Charge Depleting (CD) or Charge Sustaining (CS) mode depending on the source of motive power. Charge depleting (CD) mode can further be categorized into CD-EV and CD-blended (CDB) modes. In the CD-EV mode of operation, the entire motive power is provided by the electric motor by discharging the energy stored in the battery and the engine is never turned on. This type of operation is often called all-electric mode or zero emission (ZE) mode because only electricity is consumed and there are no tail-pipe emissions. Depending on the powertrain configuration, road network topology, speed and acceleration characteristics, and driver behavior, the engine may turn on to partially assist the motor in meeting the total propulsion energy demand in the CD mode. This is called CDB mode of operation because both electricity and gasoline are consumed, and the motive power is provided by the electric motor and the ICE. The CD mode of operation continues until the battery is depleted, after which the PHEV is operated in the CS mode as a regular HEV with the ICE providing the entire propulsion energy demand and only gasoline is consumed. Driving in the CD mode could be entirely electric VMT (eVMT) or a combination of electricity and gasoline (gVMT) VMT, whereas CS mode comprises of only gVMT. The fundamental concept of UF, assumptions, and its applications domestically and outside the U.S. is elaborated in Sections 2.2 so omitted for the sake of brevity.

Due to its simplistic and selective set of assumptions, the J2841 may not adequately reflect how PHEVs are driven and charged in real-world conditions. Using year-long longitudinal data collected via on-board data loggers from 153 PHEVs (11–53 miles AER) in California, this chapter systematically examines the disparities between observed PHEV driving, charging behavior and generalized expectations about their usage patterns, and its implications on UF estimates encapsulated in existing PEV policies. Prior studies that relied on cross-sectional travel survey data like the NHTS broadly focused on understanding the sensitivity of UF to different assumptions about travel patterns and charging behavior. In [13] alternatives to the J2841 UF is proposed using the 2009 NHTS instead of the 2001 NHTS and a mid-day opportunistic charging, typically at the workplace, is also considered. Their study reported that the proposed UF is higher than the J2841 UF, but only for PHEVs with AER less than 65 miles. While the J2841 UF is strictly a distance based metric, Ref. [14] proposes an energy based UF. Sensitivity of UF to different vehicle attributes such as age, class, annual VMT, and charging behavior depending on dwelling unit type is examined, and their analyses indicates that UF is largely insensitive to vehicle class and dwelling unit type, but highly sensitive to annual VMT, age, and charging behavior [14]. With the availability of real-world driving data collected using loggers albeit from ICEs, efforts have been undertaken to develop a more realistic PHEV driving cycle compared to dynamometer cycles [10] in order to better estimate their real-world energy consumption and emissions [15]. The scope of such efforts expanded by incorporating additional charging opportunities based on dwelling times and location. High resolution GPS enabled travel data collected over a span of 18 months from 400 ICEs in the Seattle metropolitan area is utilized in [16] to investigate how UF would change if only home based tours are considered. Their study reports that gasoline and electricity prices have no statistically significant impact on the UF, and that workplace or away from home charging increases the UF only if the AER of PHEV is less than 40 miles. Studies also applied UF by utilizing longitudinal data from ICEs for evaluating the life-cycle costs, emissions, and value proposition of PHEVs [17,18], and optimal battery size design and its impact on market acceptance [19,20].

Around early 2011, a nationwide PEV demonstration and charging infrastructure deployment was undertaken as part of the EV project [21,22] to understand Chevrolet Volt and Nissan Leaf usage patterns across 20 different U.S. metropolitan regions. This was the first project at such a scale that offered insights into the performance PHEVs by directly observing their actual usage via telematics loggers. In [21] it is reported that the observed UF of approximately 800 Chevy Volts with 35 miles AER (2011–2012 model years) and 600 Chevy Volts (2013 model year) with 38 miles AER was higher than their respective SAE J2841 UF counterparts by at least 6%. Fewer share of long-distance travel days compared to the 2001 NHTS and charging more than once per day were attributed to be the reasons for deviating from J2841 UF estimates. A study of close to 60,000 Chevy Volts (2011–2014 model years) reported that the observed Volts were able to travel 74% of their total miles in CD-EV mode alone [23]. Charging more than once per day by taking advantage of day time opportunities was identified to be the major reason for exceeding the J2841 UF and EPA sticker label fuel economy estimates similar to the findings of [21,22]. In [24] a real-world fuel economy and UF of five PHEV models with 11–38 miles of AER is analyzed and their analysis indicates that deviation from certification cycle fuel economy were reported to be anywhere between 2% to 100% depending on the AER.

Most of the literature on PHEV usage focused on energy, emissions, and value proposition mainly from the perspective of driving. Reliable access to charging infrastructure is also important factor, because apart from user preferences, it is the availability of charging infrastructure that determines charger utilization and the charging demand. Understanding when, where, how long PHEVs are charged, and what the anticipated charging demand is are important factors for charging infrastructure developers from cost recovery, charger accessibility, user's willingness to pay for charging, and charger utilization perspectives [25]. Utility companies are particularly concerned about the additional demand imposed on the grid from charging, as it has the potential to create localized hot spots if not managed properly, necessitating network upgrade or expansion. This highlights the importance of deploying coordinated or smart charging strategies that incorporate not only the economics of charging but also user preferences for charging location, time of day, duration of charging, and charging power levels [26]. Of concern are the competing objectives between the charging infrastructure developer and the user. The charging infrastructure developer seeks to minimize the cost of charging, which includes the fixed installation costs as well as the varying operating cost of providing electricity at the outlet. The PHEV driver, on the other hand, would like to maximize the convenience of charging without having to wait for a long duration, while simultaneously accomplishing this task at the lowest possible cost [27].

In summary, apart from the J2841 assumptions, the nature of travel data (longitudinal or cross-sectional), duration of data-collection, mode of data acquisition (self-reported trip diaries, data loggers with or without GPS), type of vehicle(s) used for data collection, and the targeted population (mainstream ICE users, actual PHEV owners or potential PHEV buyers) will also have consequential impacts on the techno-economic, electrification, and environmental benefits of PHEVs. The significance of UF cannot be understated since it is the vital environmental performance metric on which many federal and state level policies such as Corporate Average Fuel Economy (CAFE) and Pavley GHG emission standards [3,28,29], zero emission vehicle(ZEV) credit allocation under the ZEV mandate [30,31], vehicle emissions and label fuel economy estimates [32,33], and California's Low Carbon Fuel Standards (LCFS) [34] rely on. The main contributions of this study are the following:

- Comparative assessment of observed PHEV driving and charging and EPA sticker label expectations and the SAE J2841 assumptions.
- Eight dominant factors (four each for driving and charging) that explains the variations in observed PHEV usage patterns are extracted using Principal Components Analysis (PCA).

- Ordinary Least Squares (OLS) regression models are formulated to test the explanatory power of the factors by including them as dependent variables and the independent variable is the difference between observed and expected UF.
- Relative importance of the extracted factors in terms of their contributions to the disparities between observed and expected UF is then quantified.
- Though dimensionality reduction using PCA and regression modeling are commonly used, their specific application in the context of real-world observational study of PHEVs and UF is a new approach that is carried out in this study.

This study advances to the body of literature that focuses on improving our understanding of the real-world UF of PHEVs by discerning influential driving and charging traits that contributes to the deviations from sticker label UF. To the best of my knowledge, compared to existing studies which limit their scope of analysis to either aggregate or daily levels [16,21,22,24,35], I focuses on explaining why real-world performance deviates from label expectations by methodically examining disparities at varying time-scales (trip/charging sessions, daily, and annual); incorporates locational aspects of charging infrastructure access and utilization and how it impacts the UF; and explores if the key driving and charging factors that introduces deviations in real-world UF from their label values are the same irrespective of the AER. The outcomes of this study will offer a realistic assessment of the real-world electrification potential of PHEVs, challenges, and/or validates conventional wisdom on PHEV usage, and subsequently their energy consumption and emissions. Understanding the causes, magnitude, and direction of differences between assumptions about PHEV usage and their observed usage will help the broader scientific community in parametric updates, calibration, and validation efforts to strengthen the representativeness or correct for the lack thereof in vehicle choice modeling [36], powertrain simulation tools [37], integrated assessment studies [38], charging infrastructure planning [39], and emissions inventory [40]. I expect the paper help in formulating policies aimed to incentivize PHEVs based on road performance and to inform automakers when exploring future vehicle design.

The assemblage of data analyzed consists of driving and charging data collected between June 2015–June 2018 from 153 PHEVs in California. Five PHEV models are examined in this study: Toyota Prius (11-mile AER), Ford CMax and Fusion Energi (20-mile AER), Chevrolet Volts (35/38 miles and 53 miles AER). The rest of the paper is organized as follows. Section 3.2 summarizes the aggregate driving and charging data and describes the quantitative methods used. Comparative assessment of observed driving and charging behavior with sticker label expectations, followed by the PCA and OLS model results are presented in Section 3.3. I discuss the findings in Section 3.4 and provide concluding remarks in Section 3.5.

3.2 Data and methods

The source of the data is from the Advanced PEV Driving and Charging Behavior project, a multi-year study to monitor PEV usage in California [41,42]. Online survey was first administered to PEV owners randomly sampled from the California Clean Vehicle Rebate Project [43] and vehicle registration records. Sub-sample of respondents were selected and GPS enabled data loggers were installed in the on-board diagnostics (OBD) port and monitored for at least a year. The data loggers report more than two dozen variables related to driving, charging, performance, and comfort. The important vehicle usage parameters relevant to this analysis are: trip and charging session start and ending time stamps and locations; trip and charging session start and end state of charge (SOC); charger level, charging duration, and charged energy; trip distances, duration, and consumption (electricity and gasoline). Since the scope of this study is on real-world performance, my analysis strictly focuses on the data from the loggers, and the respondent's home location is the only relevant survey information that I included. Five PHEV models with sticker label AER varying from 11–53 miles [44] are in the dataset: Toyota Prius (11 miles AER, N = 22), Ford CMax Energi (20 miles AER, N = 28), Ford Fusion Energi (20 miles AER, N = 24), Chevrolet Volts (35/38 miles AER, N = 43; 53 miles AER, N = 36). The 35- and 38-mile AER Chevy Volts were grouped together as Volt-35/38 since there was little difference between their AER capabilities. The PHEV models analyzed in this study accounted for close to 85% of rebates issued to PHEVs under the California Clean Vehicle Rebate Project [43].

3.2.1 Driving and charging data

Table 3.1 presents the driving and charging data which consists of approximately 2 million VMT, 200,000 trips, 52,000 charging sessions, and 260 MWh of charging energy collected over the course of 45,000 driving days (driving and charging or driving only) between June 2015–June 2018 in California. On average, every vehicle in the dataset was driven 292 days, and among the PHEV types it varied between 268 and 315 days during the data collection period. Of the 52,237 charging sessions, 53% were at Level 1(L1), 1.4 kW rated and the rest were at Level 2 (L2), 3.3 kW rated [90]. Throughout the rest of the paper, unless otherwise specified, J2841 UF [33], AER and mode specific energy consumption, kWh/mile in CD-EV mode or Miles Per Gallon(MPG) in CS mode, found in EPA fuel economy labelling data [88] are collectively addressed as Expectations. The label UF refers to the EPA sticker label city/highway combined UF. Corresponding values estimated from the data analyzed in this study as Observed.

Table 3.2 presents the average annualized and daily estimates of key PHEV driving and charging metrics.

Table 3.1 Aggregate driving and charging data.

				Distance in Miles		**Charging (L1 and L2)**		**L1/L2 Share (%)**
PHEV Model	**N**	**Driving Days**	**Trips**	**VMT**	**eVMT**	**Sessions**	**Charged kWh**	**Sessions**
Prius-11	22	6921	33,421	315,166	46,573	7677	17,618	92/8
Cmax-20	28	7516	33,434	322,526	122,732	9796	36,100	57/43
Fusion-20	24	6972	34,028	346,720	108,136	9615	34,528	48/52
Volt-35/38	43	12,574	53,274	557,498	355,048	15,292	96,046	47/53
Volt-53	36	10,663	47,475	414,803	281,372	9857	73,956	33/67
Total	153	***44,646***	***201,632***	***1,956,713***	***913,862***	***52,237***	***258,248***	

Table 3.2 Average annualized and daily driving and charging metrics.

	Annualized			**Average daily**		
PHEV Model	**eVMT**	**gVMT**	**VMT**	**Charging Sessions**	**Charged kWh**	**VMT**

Prius-11	2456	14,165	16,621	1.12	2.6	45.5
Cmax-20	5960	9703	15,663	1.32	4.9	42.9
Fusion-20	5661	12,489	18,151	1.39	5.0	49.7
Volt-35/38	10,306	5877	16,183	1.23	7.8	44.3
Volt-53	9632	4567	14,199	0.95	7.1	38.9

Principal Component Analysis (PCA) is a statistical procedure to reduce the dimensionality of the dataset and it falls under the larger umbrella of Exploratory Factor Analysis (EFA). In this chapter, I used PCA to reduce the dimensionality of the observed driving and charging data which is highly susceptible to the problem of multicollinearity. Since Utility Factor is the ratio of eVMT to VMT and eVMT is a function of charging behavior, multicollinearity would persist and as such could severely undermine interpreting the statistical significance of driving and/or charging related independent variables (IV) on the dependent variable (DV). Combining both driving and charging related usage metrics and then performing the PCA may not eradicate the problem of multicollinearity. A correlation that existed in the higher dimensional space of the original data merely gets transformed and projected onto a new and lower- dimension space. This could complicate factor definition, number of factors to retain, determining the minimum loading criteria, and the rotation method to choose. To address these issues, I performed PCA of driving and charging related variables separately.

3.2.2 Principal component regression

The EFA involves four major steps. The first step is to check the appropriateness of the dataset for factor analysis. For this, I used the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (MSA) [122, 123] and Bartlett's Test for Sphericity [124]. The KMO MSA is an index between 0–1 which quantifies the ratio of observed correlations to partial correlations, the higher the better indication of the suitability of PCA [125, 126]. Literature recommends a empirical rule of thumb of at least 0.6 as a minimum for the KMO MSA [127, 128]. Bartlett's Test for Sphericity tests the hypotheses that the correlation matrix is an identify matrix, thereby implying that variables are unrelated and not suitable for PCA. Bartlett's test with a p-value of less than 0.05 is required for PCA. The KMO and Bartlett's tests together determine whether the underlying structure of the dataset is suitable before proceeding to perform the PCA. The second step is to decide how many factors to retain. The number of factors to extract and retain is typically determined based on the share of variance explained by each of the factors and a suitable threshold for the cumulative total variance captured by the PCA. Scree plot for Eigen Value of greater than one is a widely used method to select the number of factors to retain, which I used as benchmark. The resultant component matrix shows the factor loadings or correlation between variables used for PCA (row-wise) and the factors (column-wise). Factor loadings outside the interval of ±0.3 are typically omitted [128, 129]. The third step is to rotate the component matrix to simplify their structure and facilitate their interpretation. There are two major categories of factor rotation, Orthogonal and Oblique [130]. In orthogonal rotation, the factors are rotated by 90° to make them un-correlated, whereas in Oblique rotation, correlation between extracted factors are permissible. Varimax and Quartimax are the commonly used orthogonal rotation methods. The Quartimax method minimizes the number of factors needed to explain each variable used in the PCA and the Varimax method of rotation causes each variable to load heavily on one factor [131-133]. I used the Varimax method because of the simplicity of interpretation. Since the factors themselves are not correlated, Varimax rotated factors can be used in assessing the explanatory power of the factors in a regression model. The fourth and final step is to suitably name the rotated factors based on the factor loadings.

The aggregate driving and charging data of 153 PHEVs was first annualized based on the number of days every PHEV was driven. Using PCA, I identified four dominant driving and charging factors, eight in total. The KMO MSA was close to 0.8 for both the driving and charging related PCA, which is considered "meritorious" [122, 125, 126]. The p-value of Bartlett's test was extremely low and lower than the significance level of 0.05 for both the driving and charging related PCA, the data is suitable for PCA. The extracted factors captured 87% of the total variance in the dataset. Variables used for PCA, extracted factors, and their definitions are detailed in Section 3.3.

To test the explanatory power of the extracted factors, I built Ordinary Least Squares (OLS) multi-variate linear regression models with the extracted factors as the independent variables (IVs), and the deviation of observed UF from label UF as the dependent variable (DVs). The dataset was divided into two based on the AER: short-range PHEVs (Prius, Ford CMax/Fusion Energi) and long-range PHEVs (Volts). OLS regressions models for short-range PHEVs and long-range PHEVs were developed separately. I carried out a-priori and post-hoc hypothesis tests and validated that the sample size and power are adequate for the given significance level (5%) and sample size for both models. To supplement the insights gathered from the regression models and gauge the practical utility rather than just their statistical significance of the IV, I performed a relative importance analysis of each of these extracted factors by quantifying their main and total effects. The main effect is the contribution by an IV to the total variance by itself, and the total effect is the contribution by an IV to the total variance in combination with other IVs [134-136]. I also examined the effect of including interaction terms in the regression models. The regression model estimates and outcomes of the relative importance analysis are detailed in Section 3.3. The PCA was done using IBM SPSS and the OLS regression modeling, and relative importance analysis were carried out using JMP Pro 15.3.

3.3 Results

In this section, I compare real-world performance of observed PHEVs with sticker label expectations from the perspectives of UF, daily driving distances and style, mode specific energy consumption, and charging behavior. Wherever applicable, I also contrast driving and charging behavior observed among the five PHEV models studied in this chapter.

3.3.1 Descriptive comparisons

Figure 3.1 depicts the UF distribution of every PHEV observed in this study. The EPA label expected city/highway combined UF is shown inset in Figure 3.1 as well. Except for the Volt-35/38, all the other PHEV models performed below EPA expectations, and the deviations were most notable in the case of short-range PHEVs (AER 20 miles or less) compared to the longer-range PHEVs (35 miles or more AER). On average, the observed UF was anywhere between 60–103% of label UF. Figure 3.2 shows the ratio of observed UF to label UF and its distribution by PHEV type. The observed UF of 82% (N = 18) of the Prius, 75% (N = 18) of Fusion, 66% (N = 24) of Volt-53, 54% (N = 15) of CMax, and

44% of Volt-35/38 (N = 19) were lower than the label UF estimates. Two interesting observations can be gleaned from Figure 3.1 and Figure 3.2. First, the range of UF deviations is higher for shorter-range PHEVs (Prius, CMax, and Fusion) compared to longer-range PHEVs (Volts); secondly, there are few short-range PHEVs that rarely or never plug in and are operated as a regular HEV. Referring to Table 2, , the annual VMT of PHEVs observed in this study is higher than estimates reported in other real-world PHEV usage studies [40, 54, 56, 137]. From Figure 3.1, we can see that except for the Volt-35/38, the UF of PHEVs observed in this study was lower than the values reported in [40, 54, 56, 137] .

Figure 3.1. Distribution of individual UF by PHEV model. Average and standard deviation of UF is indicated within parentheses. EPA label city/highway combined UF is shown inset.

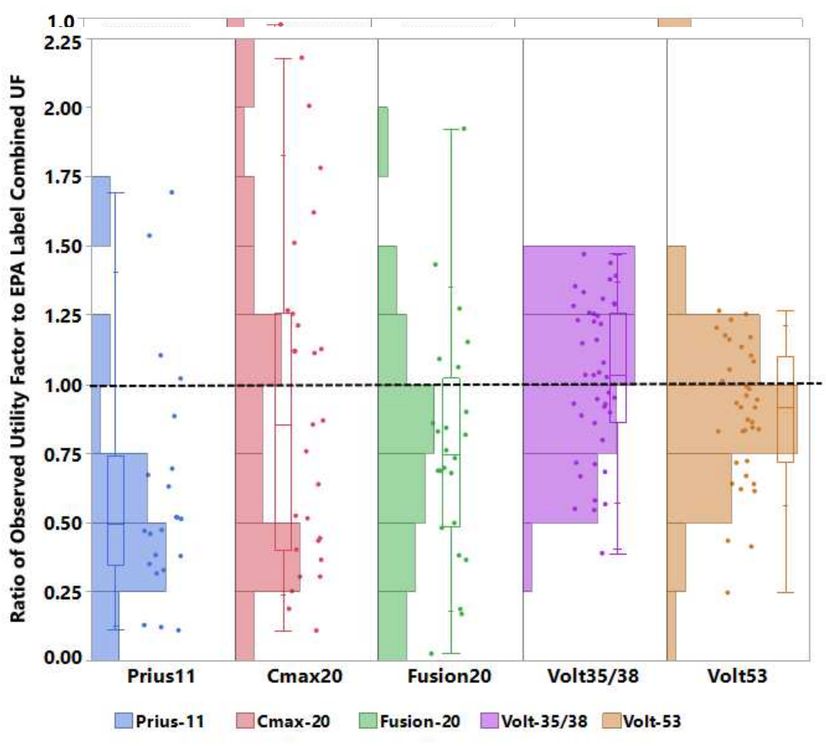
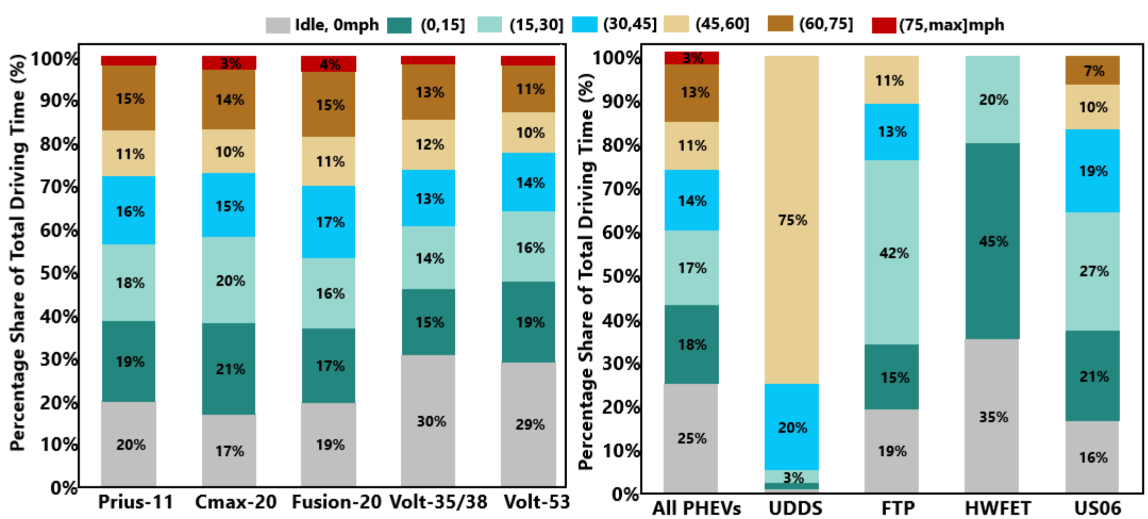


Figure 3.2. Ratio of observed UF to EPA label city/highway combined UF by PHEV model. Values above one indicates observed UF of PHEVs exceeded EPA estimates

3.3.2 Comparison with EPA certification cycles

Figure 3.3(a) shows the percentage share of total driving time based on driving speed in mph of the observed PHEVs and Figure 3.3(b) depicts the share of total driving time by driving speed of certification cycles commonly used in fuel economy and exhaust emissions measurements. The Urban Dynamometer Driving Cycle (UDDS) and Highway Fuel Economy Testing (HWFET) represent urban/city driving cycle and highway driving conditions (under 60mph) respectively [10,29,63]. The Federal Test Procedure (FTP) is an extension of the UDDS which consists of the UDDS followed by the first 505 seconds of the UDDS. The US06 is a high speed and acceleration aggressive highway driving cycle used by the California Air Resources Board (CARB) to determine additional credit allocation under its ZEV mandate[64]. Driving style within the context of this study refers to attributes such as stop frequency per mile, percentage share of driving time and distance driven at different speeds.



(a) (b)

Figure 3.3 Percentage share of total driving time by driving speed in mph: (a) Observed PHEVs; (b)Comparison with EPA Test Cycles

Figure 3.3 indicates some clear trends and divergences among the observed PHEVs as well as between the observed PHEVs and test cycles. Volts (Volt-35/38 and Volt-53 combined) have a higher fraction of idling time and lower fraction of time in highway driving conditions (60mph or more) compared to shorter-range PHEVs. We can observe a certain level of conservativeness in driving style by the Volt-53 if we compare their share of time at different speeds, which gradually decreases with increase in speed. It can be noticed from Figure 3.3 that the test cycles do not adequately capture how the driving style varies among PHEVs with different AER capabilities. Moreover, the test cycles either underestimate or completely exclude the share of driving at highway speeds (60mph or more).

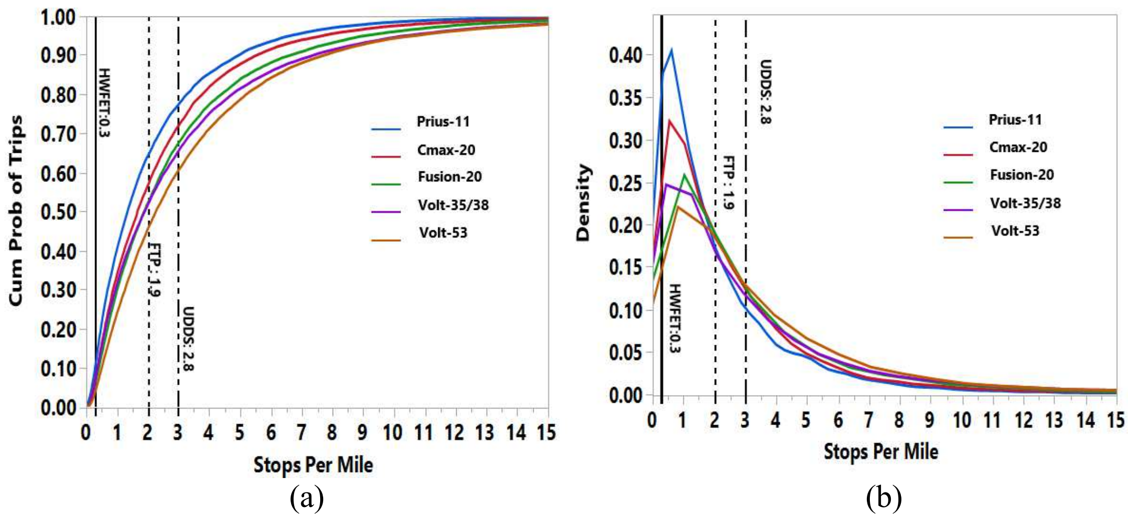


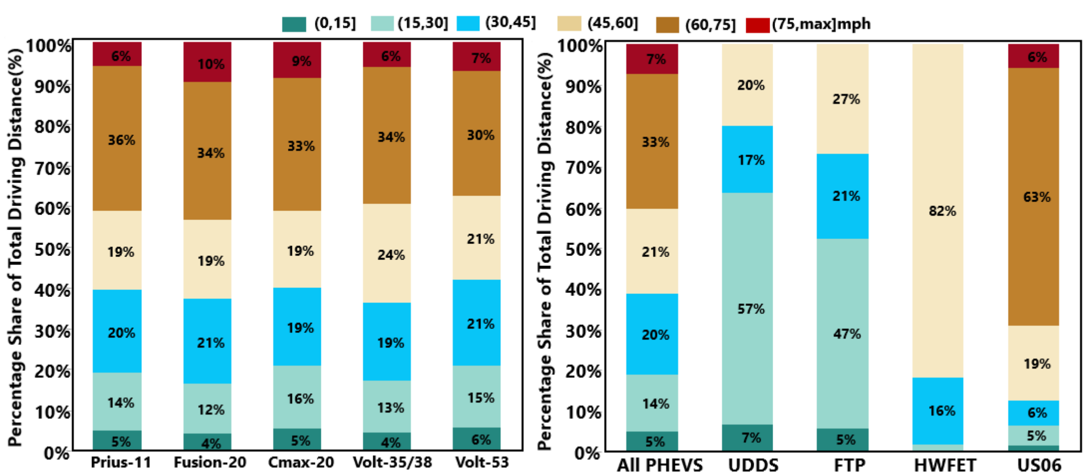
Figure 3.4 Distribution of stops per mile. (a) Cumulative distribution function (CDF); (b) Density plot. Vertical lines are drawn to indicate representative highway and urban drive cycles stops per mile.

Figure 3.4 shows the distribution of stops per mile at a trip level. Figure 3.4(a) shows the cumulative distribution and Figure 3.4(b) shows the probability density function. For reference, stops per mile of HWFET, UDDS, and FTP is also indicated in Figure 3.4 . It is interesting to note that the share of trips made with stop frequency lower than UDDS stop frequency per mile increases with AER, and varied from 60% for the Volt-53, to 75% for the Prius.

(a) (b)

Figure 3.5 Percentage share of total driving distance by driving speed in mph: (a) Observed PHEVs; (b)Comparison with EPA Test Cycles

Figure 3.5(a) shows the percentage share of total distance driven at different speed intervals among the observed PHEVs and Figure 3.5(b) shows the percentage share of total distance driven at different speed intervals under EPA test cycles. Approximately 40% of total distance was driven at highway speeds (60 or more mph) and the shorter-range PHEVs had a slightly higher share of travel at 60mph or more compared to the Volts. As found in Figure 3.5(b), majority of the city/urban or highway test cycles overestimate the share of travel at 45mph or less, especially UDDS in the case of travel at 15-30mph. Figure 3.3- Figure 3.5 clearly illustrate that the test cycles are more conservative when compared



to real-world driving style of PHEVs. The gap between observed driving and test cycles, especially highway speed driving, manifests in the form of deviations in real-world fuel economy and UF.

Table 3.3 Comparison of label expected and observed ZE and CS mode energy consumption

	CD-EV or ZE Mode Trips kWh/mile			CS Mode Trips MPG		
	Label	**Observed**	$\left(\frac{Observed}{Label}\right)$	**Label**	**Observed**	$\left(\frac{Observed}{Label}\right)$
Prius-11	0.29	0.33	87.9%	50	48	96.0%
Cmax-20	0.37	0.39	94.9%	38	40	105.3%
Fusion-20	0.37	0.40	92.5%	38	40	105.3%
Volt-35/38	0.35	0.36	97.2%	37	34	91.9%
Volt-53	0.31	0.38	81.6%	42	38	90.5%

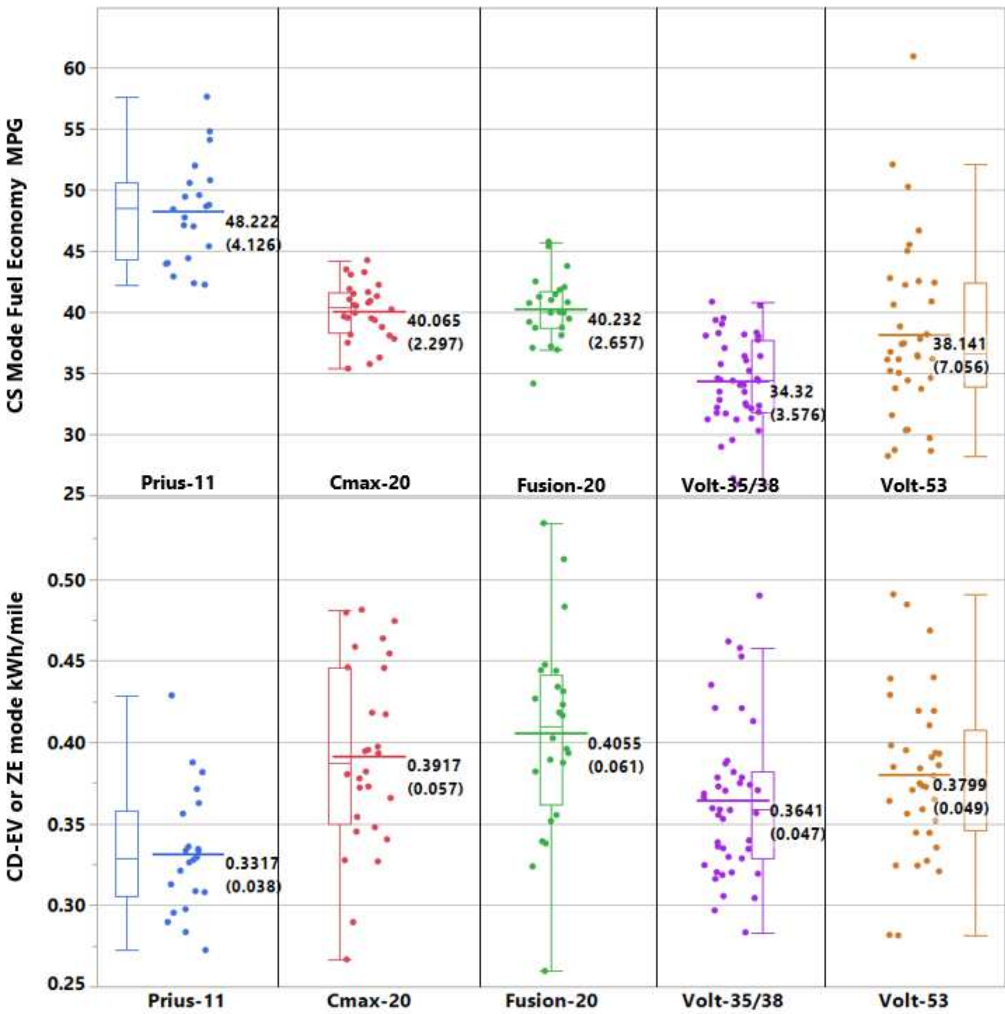


Figure 3.6 Distribution of real-world fuel economy (MPG) in CS mode trips and electricity consumption in CD-EV or ZE mode (kWh/mile) trips.In the ZE mode the engine was never turned on and CS trips was accomplished entirely on gasoline. Values adjacent to the solid dashed line show the average and standard deviation. Since high speed driving consumes more energy (gasoline and/or electricity) compared to city or stop and go driving, the effective AER, fuel economy, and UF realized on-road by a fully charged PHEV could be lower than their respective sticker label estimates. This is highlighted in Table 3.3 and Figure 3.6. Table 3.3 compares the label and observed CS mode fuel economy in miles per gallon (MPG) and CD-EV or ZE mode per mile electricity consumption (kWh/mile) and Figure 3.6 shows their respective distributions of the CS mode MPG and CD-EV mode kWh/mile observed. On average the observed CS mode fuel economy and ZE mode electricity consumption per mile was lower than the sticker label values for the

Prius and Volts (Volt35/38 and Volt-53). In the case of CMax and Fusion, their CS mode fuel economy was slightly higher than sticker label values but their CD-EV mode kWh/mile was lower than the label values. From Table 3.3, we can infer that the disparities between label and observed ZE mode kWh/mile translates into the effective AER realized on road being 3%-18% lower than of label AER. In the proceeding sub-sections, I specifically focus on driving and charging varied among the five PHEV models analyzed in this chapter.

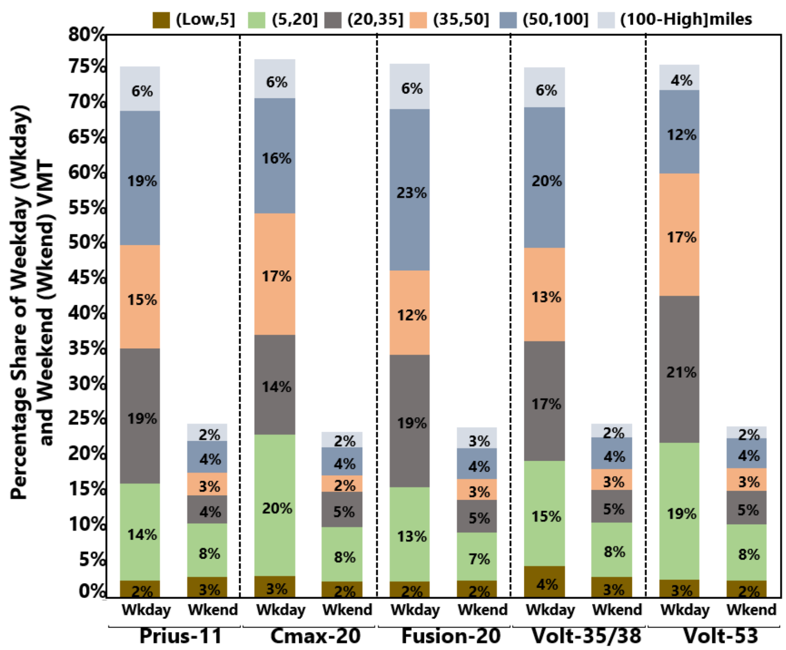


Figure 3.7 Percentage share of total VMT by distance traveled on weekdays and weekends

3.3.3 Daily VMT comparisons

Figure 3.7 shows the percentage share of total VMT categorized by distance and type of day (weekday or weekend). Using the criteria of daily VMT of 50 miles or more to define long-distance travel (LDT)[138], the share of LDT (50 miles or more) was highest for the Fusion(37%) and lowest for the Volt-53 (21%). Overall, daily travel of 50-100 miles contributed the most (24%-27%) to the share of total VMT (weekday and weekend combined) for the Prius, Fusion and Volt35/38. In the case of CMax and Volt53, daily travel of 5-20 miles contributed the most to the share of total VMT (28%). Referring to Figure 3.7, it is interesting to note that on weekends, all the five PHEV models had similar or comparable share of travel across all distance bins. If I examine the weekday travel by distance bins, daily travel of 50-100 miles still contributed the most (19%-23%) to the share of weekday VMT for the Prius, Fusion and Volt35/38. Relatively shorter driving distance of 5-20 miles dominated the share (20%) of weekday travel for the CMax and in the case of Volt-53, 20-35 miles of daily travel contributed the most (21%) to weekday VMT.

The cumulative effect of travel distance preferences depending on type of day is reflected in Table 3.4 which summarizes the daily VMT distribution by type of day. The average weekday VMT was higher than the average weekend VMT for all PHEV models expect for the CMax and Volt-53, which were driven roughly the same 43 miles and 39 miles respectively, on weekdays and weekends. Fusions had the highest average daily VMT and the Volt-53 had the lowest average daily VMT, irrespective of the type of day. From Table 3.4, it can be seen that the AER had little or no impact on the average, median or the standard deviation of VMT of Volt-35/38 and Volt-53.

Table 3.4 Daily VMT Summaries by type of day

	Weekdays		*Weekends*		*Overall*	
	Average± Std. Dev	Median	Average± Std. Dev	Median	Average± Std. Dev	Median
Prius-11	46.7±42.8	37.8	42.1±51.8	27.0	45.5±45.2	35.1
Cmax-20	42.9±37.3	35.2	43.0±58.5	24.2	42.9±43.2	33.7
Fusion-20	50.3±44.6	39.0	48.0±61.0	28.6	49.7±49.1	36.5
Volt-35/38	45.9±39.6	36.6	39.7±47.0	25.1	44.3±41.7	33.6
Volt-53	39.0±39.4	30.8	38.4±47.1	24.1	38.9±41.4	29.2

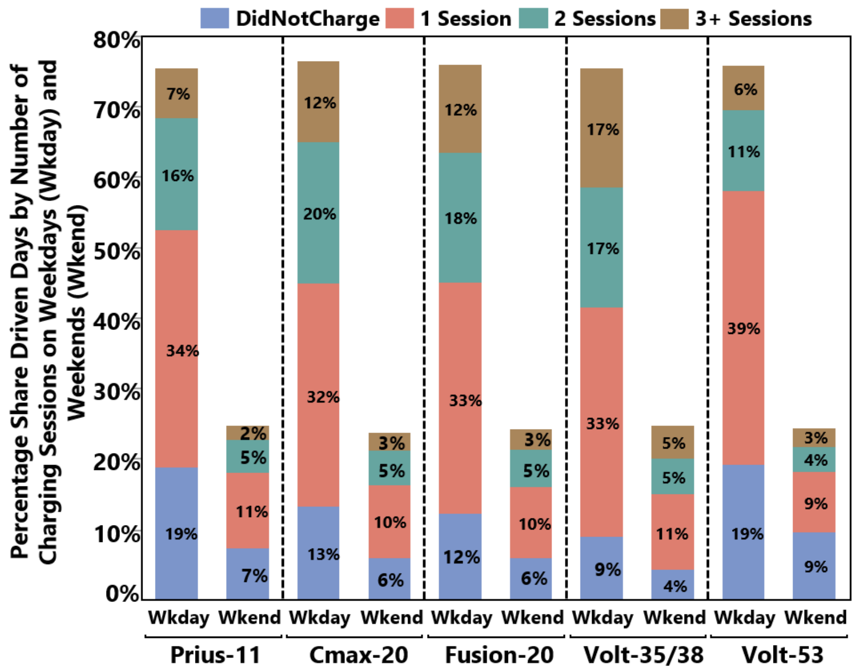


Figure 3.8 Percentage share of driven days by number of charging sessions on weekdays and weekends

3.3.4 Charging frequency and travel day starting SOC

Figure 3.8 depicts the percentage share of driving days by number of charging sessions on weekdays and weekends. If I compare Figure 3.7 with the J2841 assumptions of one charging session per day, it is very clear that the differences in charging behavior are salient. The J2841 method for UF estimation ignores two situations depicted in Figure 3.8: i) days when the PHEV was not charged at all; and ii) days when the PHEV charged more than once. Only on approximately 42%-47% of the driving days (weekdays and weekends combined) the PHEV charged at least once, on all other days, the observed daily charging frequency did not align with the J2841 assumptions of one charging per day. While conventional wisdom would suggest that shorter-range PHEVs (Prius, Cmax and Fusion) will have a higher proportion of days when they charged more than once due to AER limitations, analysis shows the counterfactual. On 44% of driving days, the Volt-35/38 charged more than once per day, whereas the CMax and Fusion charged more than once on 39% of the driving days, and the Prius charged only on

30% of the driving days. Depending upon the AER, on 13%-26% of driving days (weekdays and weekends combined), PHEV did not charge at all.

The J2841 also assumes that the travel day starts with the fully charged battery. The effect of travel day starting state of charge (SOC) of the battery on the daily VMT and eVMT is illustrated in Figure 3.9. Empty battery refers to SOC of 5% or low and full battery refers to SOC of 95% or more. We can observe from Figure 3.9 that there are three additional situations that the J2841 does not address or adequately capture: i) PHEV driven as conventional HEV when travel day starts with an empty battery; ii) possibility that the PHEV might charge away from home; and iii) possibility for intra-day charging outside of overnight parked at home time windows, typically mid-day at workplace or any other non-home location. Figure 3.10 reveals that on average, PHEVs drive longer when travel day starts with an empty battery compared to travel days starting with a fully charged battery. Except the Volt-53, all other PHEVs drive on average more than 50 miles when starting their travel day on an empty battery. We can also see that the average eVMT of Volt-35/38 and Volt-53 are almost similar on days when travel starts with a fully charged battery.

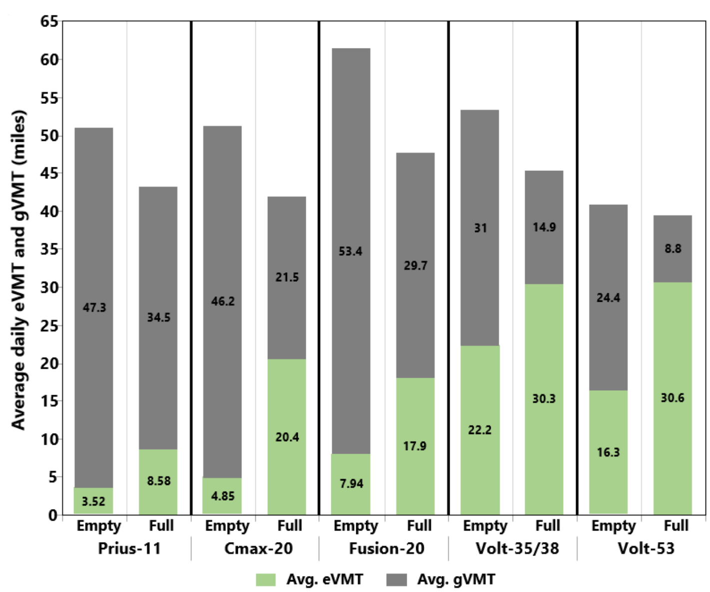


Figure 3.9 Impact of Travel Day Starting SOC on Average daily eVMT and gVMT

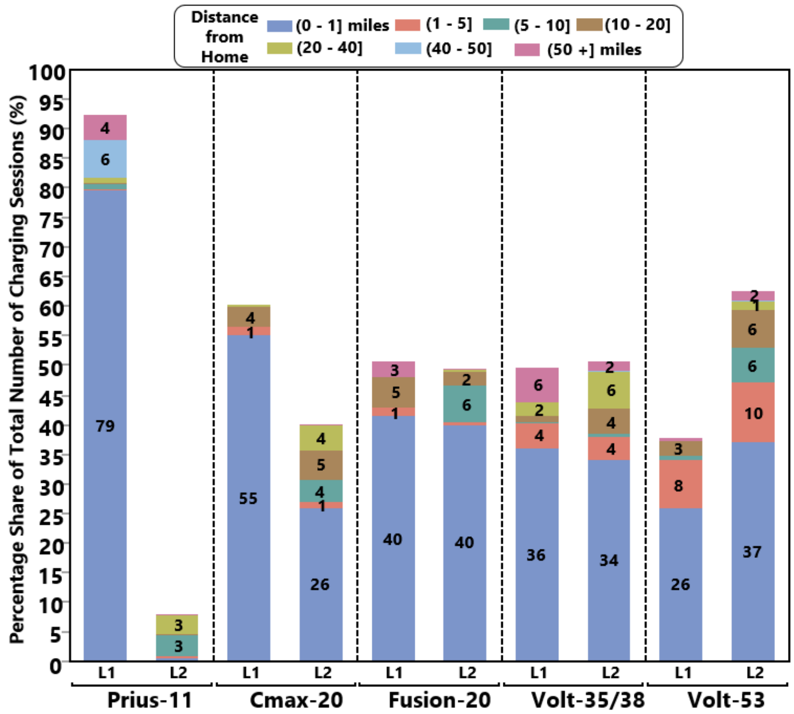


Figure 3.10 Percentage share of L1 and L2 charging sessions by distance from home. Values less than or equal to 1% have been omitted for clarity. Distances are the great-circle distances calculated using the Haversine formula. *Charging location distance from home*

Figure 3.10 portrays the percentage share of charging sessions by charger level and distance from the home location. Out of 52,237 charging sessions, 46,137 had valid GPS data. The percentage share by distance from home indicate Figure 3.10 is based on these 46,137 sessions. Overall, roughly 74% of all charging sessions (L1 and L2 for all PHEVs combined) occurred at locations that are less than a mile (great-circle distance) from home. Close to 80% of charging sessions (L1 and L2 combined) happen within 1 mile of the home location for Prius, CMax and Fusion. In the case of Volt-35/38 and Volt-53, the share of charging sessions less than a mile from home was 70% and 63% respectively. In terms of charger utilization by charger level, level 1 charging was the most frequently used by Prius and CMax as it accounts for 90% and 60% of their total number charging sessions respectively. Even though the Fusion also has the same 20-mile AER as CMax, it had an equal share of charging at L1 and L2, like the Volt-35/38. Close to 60% of Volt-53 charging sessions were at L2 and 25% of which occurred at locations more than a mile away from the home location. Approximately 90% of CMax and Volts (Volt-35/38 and Volt-53), 88% of Fusion, and 83% of Prius charging happened at locations that are less than their respective AER. Home or close to home seems to be the most preferred location for irrespective of AER.

3.3.6 PCA of driving and charging behavior

The goal of PCA is to deduce the most important driving and charging traits that significantly impact the UF and thereby its deviation from label UF. Since UF is the ratio of eVMT to VMT and eVMT is intricately linked to charging behavior, I perform PCA on driving and charging separately. In order to adequately represent important VMT indicators such as annual mileage, driving style (highway or stop and go city dominant), and long-distance travel needs, the following variables were used:

i. Annual VMT (miles)
ii. Share of annual VMT at 55mph or faster (%)
iii. Long-distance travel (LDT) 100 miles or more share of annual VMT (%)
iv. Daily VMT 50 miles or less share of annual VMT (%)
v. Average number of stops per mile

Table 3.5 summarizes the PC loadings, Eigen values, and the cumulative percentage of variance captured. The criteria to evaluate the suitability of data structure for PCA are indicated in Figure 3.5. KMO MSA index of 0.8 is considered as *"meritorious"*[122, 125, 126] , and KMO MSA of 0.711 yields reliable factors[139]. The KMO MSA was 0.799 and the p-value of Bartlett's test was extremely low and lower than the significance level of 0.05 so the data is suitable for PCA.

Table 3.5 PCA of Driving Behavior: Unrotated and Rotated PC Loadings, Eigen Values, and Percentage of Variance (σ^2) Captured

PC	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotated Sums of Squared Loadings		
	Total	*% of σ^2*	*Cum. % σ^2*	*Total*	*% of σ^2*	*Cum. % σ^2*	*Total*	*% of σ^2*	*Cum. % σ^2*
1	3.27	65.3	65.3	3.27	65.3	65.3	1.20	24.0	24.0
2	0.70	14.0	79.4	0.70	14.0	79.3	1.09	21.8	45.9
3	0.49	9.8	89.2	0.49	9.8	89.1	1.07	21.3	67.2
4	0.39	7.8	97.0	0.39	7.8	97	1.03	20.6	87.8

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser normalization. Rotation converged in 5 iterations. Kaiser-Meyer-Olkin(KMO) Measure of Sampling Adequacy(MSA) = 0.799 ;
Bartlett's Test of sphericity: χ^2 =406.410, df =10, p < 0.000

Using the Scree test for Eigen values greater than 1 [140], four factors were retained which capture 88% of total variance and each factor roughly captures a similar proportion of variance. Table 6 summarizes the Varimax rotated factor loadings. The KMO MSA of the individual driving related variables was at least 0.74. For notational convenience, the four factors extracted are named with the suffix *.Drv* in Table 3.6.

Table 3.6 PCA of Driving Behavior: Varimax Rotated Factor Loadings and Influential Driving Traits Extracted

Variables*	*KMO MSA ***	PC1.Drv	PC2.Drv	PC3.Drv	PC4.Drv
Annual VMT (miles)	*0.752*	<u>0.872</u>	0.237	-0.266	0.232
Share (%) of Annual VMT at 55mph+	*0.856*	0.231	0.222	-0.269	<u>0.892</u>
Long-distance travel(LDT) 100 miles or more share (%) of annual VMT	*0.89*	0.21	<u>0.939</u>	-0.105	0.195
Daily VMT 50 miles or less share (%) of annual VMT	*0.74*	<u>-0.54</u>	<u>-0.305</u>	0.227	-0.291
Average Stops Per Mile	*0.848*	-0.228	-0.107	<u>0.928</u>	-0.241
		High Usage intensity	*Long-distance travel*	*Conservative driving*	*High energy intensity*

**All variables are annualized unless otherwise specified. ** KMO MSA of individual variable*
Significant loadings (absolute loadings greater than 0.3) shown in <u>bold and underlined</u>

Based on the relative magnitude and direction of loading, the underlying factors can be described as follows. Loading of annual VMT is highest on PC1.Drv and it represents the high usage intensity. The loading of long-distance travel 100 miles or more share of annual VMT on PC2.Drv is highest, whereas the loading of daily VMT 50 miles or less share of annual VMT is significant but negative on PC2.Drv. PC2.Drv thus represents driving behavior characterized by strong preferences for long-distance travel. The variable with the highest loading on PC3.Drv is the average stops per mile. Annual VMT and share of VMT at high speeds loads negatively on PC3.Drv, but not significant, and conservative driving style is captured by PC3.Drv. Since the share of VMT at 55mph or more loads heavily on PC4.Drv, it concerns with the energy intensity of driving and inclination for high speed driving.

Charger accessibility and utilization are key indicators of charging behavior and subsequently eVMT. In order to uncover these, the following variables were selected for the PCA of charging behavior:

i. Away: charged energy (kWh)
ii. Away: Number of charging sessions
iii. Away: Charging duration (minutes)
iv. Share of charging at away locations (%)
v. Home: charged energy (kWh)
vi. Home: Number of charging sessions
vii. Home: Charging duration (minutes)
viii. Number of days vehicle charged both at home and away locations

Where home based refers to locations that are less than a mile from home and away refers to all non-home locations. Charged energy, number of sessions and duration include both L1 and L2 charging.

Table 3.7 PCA of Charging Behavior: Unrotated and Rotated PC Loadings, Eigen Values, and Percentage of Variance (σ^2) Captured

PC	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotated Sums of Squared Loadings		
	Total	*% of σ^2*	*Cum. % σ^2*	*Total*	*% of σ^2*	*Cum. % σ^2*	*Total*	*% of σ^2*	*Cum. % σ^2*
1	4.3	53.5	53.5	4.3	53.5	53.5	2.9	35.7	35.7
2	2.0	24.6	78.1	2.0	24.6	78.1	1.8	22.2	57.9
3	0.8	9.5	87.6	0.8	9.5	87.6	1.2	15.5	73.3
4	0.4	5.0	92.6	0.4	5.0	92.6	1.1	13.8	87.2

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser normalization. Rotation converged in 6 iterations. Kaiser-Meyer-Olkin(KMO) Measure of Sampling Adequacy(MSA) = 0.797 Bartlett's Test of sphericity: χ^2 =1015.83, df =28, p < 0.000

Table 3.8 PCA of Charging Behavior: Varimax Rotated Factor Loadings and Influential Charging Traits Extracted

Variables*	*KMO MSA*	PC1.Chg	PC2.Chg	PC3.Chg	PC4.Chg
Away: charged energy (kWh)	*0.821*	0.909	-0.121	-0.173	0.108
Away: Number of charging sessions	*0.803*	0.853	-0.188	-0.047	0.307
Away: Charging duration (minutes)	*0.811*	0.954	-0.116	-0.162	-0.013
Share of charging at away locations (%)	*0.876*	0.492	-0.338	-0.407	0.008
Home based: charged energy (kWh)	*0.761*	-0.158	0.752	0.537	0.081
Home based: Number of charging sessions	*0.788*	-0.242	0.336	0.822	0.284
Home based: Charging duration (minutes)	*0.781*	-0.164	0.952	0.128	0.071
Number of days vehicle charged both at home and away locations	*0.565*	0.197	0.104	0.184	0.953
Charger Accessibility		*Away*	*Home*	*Home*	*Home and away*
Charger Utilization: Charging Frequency		*Frequent*	*Less frequent*	*Frequent*	*Balanced*
Charger Utilization: Charge Cycle		*Deep*	*Deep*	*Shallow*	

**All variables are annualized unless otherwise specified. Charging sessions, duration, and charged energy include both Level 1 and Level 2. Significant loadings (absolute loadings greater than 0.3) shown in bold and underlined*

Table 3.7 summarizes the PC loadings, Eigen values, and the cumulative percentage of variance captured by the PCA of charging behavior. Similar to the PCA of driving behavior, the suitability of data for PCA of charging behavior was validated. The Scree test for Eigen value criterion one was used and four factors were retained, which capture 87% of total variance. Table 3.8 summarizes the Varimax rotated factor loadings and the influential charging traits extracted by the PCA. From Table 3.8 , we can see that all away charging related variables load positively on PC1.Chg and are significant. Likewise, loading of all home charging related variables are positive and significant on PC2.Chg. Though the loading of home charging related variables on PC3.Chg is comparable to its loading on PC2.Chg, there is an important distinction between them. The loading of home charging duration is positive, significant and numerically greater on PC2.Chg compared to PC3.Chg. In contrast, the loading of number of home charging sessions is positive, significant and numerically greater on PC3.Chg compared to PC2.Chg. Higher the loading of charging duration, longer is the charging duration, and thereby implying deep charge cycles. Likewise, higher loading of number of charging sessions indicates higher frequency of charging. The Number of days PHEV charged at both home and away location is strongly correlated with PC4.Chg and the loading is significant. This is indicative of enhanced charger accessibility at both home and away. The number of away charging session and to an extent the number of home charging session is also positively associated with PC4.Chg, though the absolute loading is only slightly below the threshold of 0.3. Based on these observations, I describe the factors based on charger accessibility, charger utilization measured in the form of charging frequency, and charger utilization measured in the form of charged duration. PC1.Chg describes frequent and deep charge cycles at away locations. PC2.Chg describes less frequent, deep charge cycles at home, and PC3.Chg describes frequent, shallow charge cycles at home, and PC4.Chg is indicative of balanced utilization of charger at home and away locations.

3.3.7 Principal component regression

The eight retained PCs are the IVs and the DV is the difference between observed UF and EPA label city/highway combined UF (ΔUF=Observed UF – label UF). The purpose of developing regression models is to understand how well the extracted PCs can explain the difference between observed and label UF and also identify which PCs contribute the most to the ΔUF and how it varied between short-range and longer-range PHEVs. Using the aggregate annualized dataset, I created OLS regression models for short-range (Prius, CMax, and Fusion) and longer-range PHEVs (Volt35/38 and Volt-53) separately. Statistical tests using G*Power 3 [95] was performed to verify and validate the following:

- *A priori*: for given significance level, effect size, and power, computing the number of samples required
- *Post hoc*: compute power achieved for the given sample size, significance level and effect size

For both regression models, all the *a priori* and *post hoc* test results confirmed that the sample size was adequate to detect a large effect size based on Cohen's *d* , and the achieved statistical power was more than 95% [141-143]. These test results are summarized in Table B1-Table in Appendix B. To ensure consistency and parity across all the hypothesis and statistical significance tests, significance level of 5% was chosen.

Table 3.9 OLS Regression Model Results: Short-range PHEVs (SRPHEVs)

DV=ΔUF ***ΔUF =Observed UF – label UF***		***Short-range(SR) PHEVs N=74***				
PCs		Estimate	Std. Error	Prob>|t|	t-ratio	Std. Estimates
	Intercept	-0.0662	0.0288	0.005	13.11	
PC1.Chg	Away-frequent and deep cycle	**0.0911**	0.0430	***0.0104****	1.8	0.1815
PC2.Chg	Home-less frequent and deep cycle	**0.047**	0.0329	0.0799	3.76	0.2842
PC3.Chg	Home-frequent and shallow cycle	**0.0531**	0.0157	***<.0001****	3.17	0.2310
PC4.Chg	Home and away-balanced utilization	**0.0593**	0.0197	***0.0004****	3.58	0.3595
PC1.Drv	High usage intensity	**-0.0703**	0.0158	***<.0001****	-5.1	-0.4024
PC2.Drv	Long-distance travel	-0.0152	0.0185	0.31	-0.11	-0.0084
PC3.Drv	Conservative driving	-0.0208	0.0273	0.346	0.95	0.0655
PC4.Drv	High energy intensity	**-0.0718**	0.0159	***<.0001****	-3.79	-0.2795
				SRPHEV Model Fit		
	$\boldsymbol{R^2}$			0.772		
	Adjusted $\boldsymbol{R^2}$			0.744		
	Root mean square error			0.103		
	Akaike Information Criterion (**AIC**)			-112.3		
	Bayesian Information Criterion (**BIC**)			-92.846		

**Factors that are statistically significant at 5%*
Std. error is standard error ; Std. estimates is the standardized estimates

Table 3.9 and Table 3.10 summarizes the regression model coefficients (β) and summary of fit for the short-range and long-range PHEVs respectively. Referring to Table 3.9 for the short-range PHEVs, except long-distance travel and the conservative driving style, all other factors were statistically significant. At 5% significance level, except the PC that describes less frequent and deep cycle home charging, all other charging related PCs have a statistically significance and positive impact on the UF of short-range PHEVs. All the four charging related PCs are have statistically significant and positive impact on the UF of longer-range PHEVs. Except the PC that describes conservative driving, all other driving related PCs have a statistically significant and negative impact on the UF of longer-range PHEVs. In the case of longer-range PHEVs, except conservative driving all other factors were statistically significant at 5%. Long-distance travel had a statistically significant impact on ΔUF of LRPHEVs but not on short-range PHEVs. When we compare the model fit, the R^2 of LRPHEV regression model is lower than that of the SRPHEV regression model even though the LRPHEV model (Table 3.10) has a slightly higher number of observations and higher number of statistically significant factors compared to the SRPHEV regression model (Table 3.9). This could potentially be due to larger variations in LRPHEV usage patterns compared to SRPHEVs.

Table 3.10 OLS Regression Model Results: Long-range PHEVs (LRPHEVs)

	DV=ΔUF ΔUF =Observed UF – label UF	***Longer-range(LR) PHEVs N=79***				
PCs		Estimate	Std. Error	Prob>|t|	t-ratio	Std. Estimates
	Intercept	-0.0423	0.0170	0.015	38.56	
PC1.Chg	Away-frequent and deep cycle	**0.0462**	0.0136	***0.0011****	3.11	0.2777
PC2.Chg	Home-less frequent and deep cycle	**0.0397**	0.0139	***0.0055****	2.47	0.2183
PC3.Chg	Home-frequent and shallow cycle	**0.0955**	0.0144	***<.0001****	5.91	0.4354
PC4.Chg	Home and away-balanced utilization	**0.042**	0.0203	***0.0385****	1.32	0.1026
PC1.Drv	High usage intensity	**-0.0894**	0.0197	***<.0001****	-4.46	-0.4077
PC2.Drv	Long-distance travel	**-0.1118**	0.0135	***<.0001****	-8.44	-0.6515
PC3.Drv	Conservative driving	0.0102	0.0118	0.386	1.46	0.1141
PC4.Drv	High energy intensity	**-0.0635**	0.0148	***<.0001****	-4.06	-0.3102
		LRPHEV Model Fit				
	R^2	0.673				
	Adjusted R^2	0.636				
	Root mean square error	0.115				
	Akaike Information Criterion (**AIC**)	-102.48				
	Bayesian Information Criterion (**BIC**)	-82.02				

**Factors that are statistically significant at 5%*
Std. error is standard error ; Std. estimates is the standardized estimates

3.3.7.1 Relative importance analysis

I ascertain the practical utility of the insights gathered from the regression models by carrying out relative importance analysis. Relative important analysis quantifies the contribution of an IV to the total predictable variance by itself (main effect) and in combination with other IVs (total effect), without making any assumptions about its statistical significance [136]. This would enable comparing the relative contribution of the eight PCs and how it varied between short-range and longer-range PHEVs. For each of the IV, Monte Carlo samples using Latin Hyper Cube sampling are obtained from its initial set of observed values and the process is iterated until the standard error of the main and total effects are below a certain threshold [144]. **Error! Reference source not found.**Table 3.11 summarizes the main and total effect of the IVs in the across the three models. The top three predictors based on the magnitude of their main effect are also highlighted in Table 3.11.

Table 3.11 Relative contribution of IVs to total predictable variance

	DV=ΔUF **ΔUF =Observed UF – label UF**	**Short-range PHEVs**		**Longer-range PHEVs**	
PCs		Main Effect	Total Effect	Main Effect	Total Effect
PC1.Chg	Away-frequent and deep cycle	0.0873	0.1022	0.06	0.0857
PC2.Chg	Home-less frequent and deep cycle	0.0138	0.0228	0.034	0.0554
PC3.Chg	Home-frequent and shallow cycle	0.1184	0.1333	**0.1973**[2]	0.2235
PC4.Chg	Home and away-balanced utilization	**0.1881**[3]	0.203	0.0123	0.0257
PC1.Drv	High usage intensity	**0.2531**[1]	0.2681	**0.1293**[3]	0.1556
PC2.Drv	Long-distance travel	0.0036	0.0073	**0.3463**[1]	0.3725
PC3.Drv	Conservative driving	0.0028	0.0062	0.0012	0.004
PC4.Drv	High energy intensity	**0.2376**[2]	0.2526	0.0675	0.0933

Inputs are independently resampled inputs using Monte Carlo. [1]Most important predictor; [2]Second most important predictor; [3]Third most important predictor

The magnitude of the main and total effects from Table 3.11 when examined in conjunction with the direction (positive or negative) of coefficient estimates in Table 3.9 and Table 3.10, provides a better picture of how dominant driving and charging traits impact the UF of short-range and longer-range PHEVs. In the case of short-range PHEVs, high usage intensity, high energy intensity, and home and away balanced utilization capture close to 65% of total predictable variance, Table 3.11. For the longer-range PHEVs, the main effect of long-distance travel accounts for 35% of total predictable variance, followed by the main effects of home-frequent and shallow cycle charging, and high usage intensity respectively. While the UF of short-range PHEVs increases with the increase in charger access at home and away locations, for the longer-range PHEVs, encouraging more home based charging has a positive effect of UF. For the longer-range PHEVs, increasing the frequency of charging at home has a much bigger and positive effect on UF compared to deep charging cycles or longer charging duration. This is attributable to their AER capabilities coupled with lower annual mileage and daily driving distances . It can be inferred from Table 3.11 that the relatively aggressive and higher energy intensity of driving has a much bigger effect on the UF of short-range PHEVs compared to the longer-range PHEVs.

3.3.7.2 Interaction effects

I investigated whether inclusion of interaction terms to the regression models improves their explanatory power. To avoid confounding and conflating, which would hinder the interpretation of independent variables, I specifically focused on the statistically insignificant driving and charging in Table 3.9 and Table 3.10. This would clearly indicate the statistical significance of the interaction term and its effect on the overall model fit, which could not have been captured in the main effects only model (Table 3.9 and Table 3.10). The variables I considered for interaction effects are Long-distance travel (PC2.Drv), Conservative driving (PC3.Drv), and Home-less frequent and deep cycle charging (PC2.Chg). Since the driving and charging PCs themselves are orthogonal due the nature of component extraction using Varimax method, and to avoid overfitting, only one interaction term (between a driving related PC and charging related PC) were considered at a time and individual regression models were developed for each of the interaction terms. In addition, I also interacted the top two predictors that contributed most to predictable variance from Table 3.11.

I developed the four additional regression models with main and interaction effects. For short-range PHEVs, the following interaction terms were considered: i) *PC2.Chg* PC3.Drv; ii) PC2.Chg*PC2.Drv* ; and iii) *PC4.Chg * PC1.Drv*. For the longer-range PHEVs since only one term was statistically insignificant *(PC3.Drv,* Table 3.10*)*, I included the top two predictors from Table 3.11, *PC3.Chg * PC2.Drv* as the interaction term. The parameter estimates and model fits of the four regression models are summarized in Appendix B, Table A3. None of the interaction terms were statistically significant at 5% and there were no noticeable improvements in the model fit. Due to these two reasons, the relative importance of the interaction terms were not analyzed further.

3.4 Discussion

I analyzed year-long driving and charging behavior of 153 PHEVs in California and compared it against EPA test cycles and SAE J2841 assumptions. I expanded upon these observations by examining usage pattern differences among the five PHEV models included in this chapter. Observed PHEVs are driven more aggressively and accomplish a higher share of travel in non-urban driving conditions (45 mph or faster or less than 3 stops per mile) compared to standardized dynamometer test cycles. The percentage share of time and distance traveled at highway speeds (60 mph or faster) is noticeably under-represented or excluded in test cycles. Approximately 80% of VMT in the UDDS cycle is at 45mph or slower, whereas the overall average was only 40%. Short-range PHEVs (Prius, CMax and Fusion) are driven 4%-7% more at 60mph or faster compared to longer-range PHEVs (Volts). The above disparities clearly manifested in the form of increased energy consumption in the CD-EV mode, which reduces the effective AER realized on-road. Using PCA, I characterized driving behavior based on 4 factors: vehicle usage intensity, aggressive driving style at highway speeds which increases the energy intensity, preference for long-distance travel, and conservative driving style.

Analysis of charging behavior revealed marked differences between the single, overnight, fully charged assumption of J2841. On average, observed PHEVs (except the Volt-53) charged more than once per day and the driving distance on days when the PHEV was not charged was more compared to the days on which they charged at least once. Results indicated that short-range PHEVs have a higher share of driving days when they are not charged at all. Possibility of PHEVs to charge away from home, charge more than once per day, and PHEV being used like a regular HEV are the other notable distinctions between this study and the generalized J2841 assumptions. The differences in charging behavior outlined above are due to charger accessibility by location (home, away or both) and charger utilization which could be defined based on frequency of charging or duration of charging. These were characterized using four influential factors extracted by the PCA. Regression models and relative importance analysis indicated that for short-range PHEVs (Prius, CMax, and Fusion), higher annual VMT and share of travel at highway speeds contributed the most to the observed UF being lower than label rated estimates, whereas enhanced charging infrastructure at home and away increases the UF. In the case of the Volts, long-distance travel days (50 miles or more) and share of travel at highway speeds were the primary reason for lowering the observed UF below its label rated estimated, and increasing the frequency of charging at home increases the UF.

Driving related differences could due to a combination of road infrastructure, early adopter preferences, and vehicle technology attributes like age, AER, maximum electric speed, and drivetrain design. California has the third highest rural interstate and the highest urban interstate highway system length[145], which was partly reflected in the relatively bigger share of highway speed driving observed in this study, compared to test cycles that are used in performance evaluation. California also scores low in proximity to major roadways[146] and ranks among the top three states by average VMT in urban and suburban census tract groups [147]. The cumulative effect of these California specific features were clearly revealed annual VMT and share of long-distance travel (50 miles or more) of the PHEVs observed in this study. The sub-sample of drivers in this dataset are PEV early adopters who purchased or leased a new PHEV and are generally more educated, wealthier, and own a home, compared to mainstream ICE user's driving patterns in the NHTS on which the J2841 relies on[148, 149]. Rebound effect in the classical sense by which improvements in fuel economy of newer vehicles increases the travel demand[150], could also have played a part in higher vehicle usage intensity of all the PHEV models compared to sticker label annual mileage of 15,000 miles, except the Volt-53, which seem to have faced a slight backfire effect[151].

Apart from differences among the PHEV models in terms of annual VMT, driving style (aggressive or conservative), and the magnitude of long-distance travel, the distribution of UF indicates that heterogeneity in charging preferences exists among different as well as within the same PHEV model. The fact that some of PHEVs irrespective of AER electrified less than 20% of their rated label UF demonstrates that motivations for charging or not charging are far more complex in reality compared to the simplistic notion of one fully charged session per day per day at home. This study illustrates that charger accessibility and utilization have varying levels of influence on the UF depending on the AER. In the case of short-range (20 miles or less, Prius, CMax and Fusion), since their AER is less than their average daily VMT (about 46 miles), there was not enough incentive in the form of eVMT gained, to charge more for compensating their higher travel demand. Lower UF of observed PHEVs compared to their rated label estimates could also be due to self-selection bias by PHEV buyers who are less concerned about eVMT because their decision to purchase the PHEV was motivated by other reasons such as rebate, clean air vehicle decals, or preferential parking spaces. It is also evident that there are diminishing marginal returns in UF and eVMT with increase in the AER. The case in point being the UF of Volt-53, which was like that of Volt-35/38, in spite of the Volt-35/38 driving 2000 miles more than Volt-53 annually.

The performance of PHEVs depends on the intertwined relationships between driving behavior, charging behavior, vehicle technology attributes, and user preferences. The dual propulsion energy source (electric motor and conventional ICE) enables the automakers to offer a wide range of design options to potential buyers depending on the degree of emphasis of one driving mode over the other, which is influenced by the policy goals. Fuel economy and energy efficiency of the ICE were prioritized over the all-electric mode operation due to cost and charging infrastructure considerations in the infant stages of the PHEV market. To maximize the GHG reduction potential of PHEVs, policies that encourage longer-range PHEVs, which emphasizes more on all-electric mode of are needed. While this has a direct impact on the policy signals sent to the automakers and subsequently the model offerings available for potential PHEV buyers, it is critical to consider aspects outside the domain of vehicle technology such as charging infrastructure expansion and heterogeneous user preferences. Though this study does not advocate moving away or replacing the J2841 UF as the metric to quantify the environmental impact of PHEVs, there is definitely room for improving the accuracy UF estimates by incorporating additional scenarios that are more representative of real-world driving and charging behavior. Generalizability and applicability of insights to the broader PHEV market in general, or even within California is not feasible due to sample size limitations, which is very common and unavoidable, and intrinsic to real-world observational studies. Moreover, today's PHEV users are early adopters, whose socio-demographic and economic indicators differ from the general population of mainstream ICE users [152].

3.5 Conclusions

This study systematically analyzed the driving and charging patterns of 153 PHEVs operating in California. The purpose of this study is to investigate why the observed performance of PHEVs deviated from their expectations and what were the influential factors that contributed to these disparities. I first compared observed with expected PHEV usage patterns. I also compared the usage patterns of the five PHEV models (Prius, CMax/Fusion Energi, first and second generation Chevrolet Volts) that were analyzed in this study at time-scales varying from trip-level to annual estimates. I utilized principal components analysis to reduce the dimensionality of the dataset while capturing at least 87% of the variance in dataset using just four driving and four charging related factors. The explanatory power and the statistical significance of the extracted factors were evaluated using multivariate regression models. I quantified the relative contribution of each of the extracted factors towards the difference in observed Utility Factor from label expected values. I also investigated if there are any statistically significance interaction terms which further improves the regression model fit and offers additional insights.

Results indicated that higher annual mileage and higher energy intensity were the top two aspects that lowered the observed UF of short-range PHEVs (Prius, CMax/Fusion) when compared to label expectations. Enhanced charging infrastructure access and balanced utilization at home and away increases the observed UF of short-range PHEVs. In the case of longer-range PHEVs (Volts), their propensity towards more long-distance travel (50 or more miles/day) followed by their annual mileage contributed the most to lowering their UF from label values. Due to their bigger battery capacity, increasing the frequency of shallow charging sessions has a bigger and positive effect on UF, rather than charging for longer-duration time but less frequently. Regression models indicated that the effect of long-distance travel and deep cycle charging at home were statistically significant for longer-range PHEVs, but not for short-range PHEVs. Analyses also indicated the absence of any statically significant interaction terms. Distribution of UF (Figures 3.1)indicates that even within PHEVs with same AER, there is a diversity in usage patterns. Daily driving distances and style (Figure 3.2-Figure 3.5), number of charging sessions on days driven (Figure 3.8), charging location distance from home (Figure 3.10), demonstrates the linkage between travel and charging behavior and AER.

Plug-in electric vehicles (BEVs and PHEVs) are essential to reduce transport sector GHG emission and energy consumption. Plug-in hybrid electric vehicles are considered as an intermediate and an enabling technology option which can catalyze large-scale adoption of PEVs. The environmental benefits of BEVs are unambiguous due to their zero tail pipe emissions, however the same cannot be said about the PHEVs. Operational and fuel-use flexibility helps the PHEVs in overcoming range anxiety related issues associated with BEVs, but the same flexibility complicates the task of evaluating their net environmental impact. To address this, the concept of UF has been developed and widely utilized in the policy domain and techno-economic assessments. There is a growing body of demonstrable evidence suggesting that a mismatch or gap exists between official EPA sticker label and real-world UF, which warrants a deeper examination to improve our estimates of the electrification potential of PHEVs. This study focused on this research need by scrutinizing real-world PHEV usage patterns and discerning salient facets of driving and charging that deviated from assumptions embodied in sticker label energy consumption and UF estimates. Superimposing a set of preconceived notions about driving and charging behavior has direct ramifications on how PHEVs are evaluated in command and control policies like the ZEV mandate, regulations governing their on-road performance, and policies that encourage their usage through economic incentives. Developments in battery technologies, diversification of PHEV model offerings, expansion of charging infrastructure, and a favorable policy environment will increase the market share of PHEVs. As the PHEV market evolves and grows, the need for observing PHEV through studies such as the I presented here will become increasingly valuable. Recognizing real-world scenarios that diverged from assumptions will better inform future policies.

4 Behavioral and Technology Implications of Electromobility on Household Travel Emissions Evidence from Revealed Preferences of Electric Vehicle Owners in California

4.1 Background

The transportation sector emitted 1,900 million metric tons of carbon-di-oxide equivalent ($MMTCO_2e$) in the U.S., roughly one-third of total greenhouse gas (GHG) emissions[153]. Nearly 60% of the total transportation sector emissions came from the light-duty vehicle (LDV) segment, which includes passenger cars(PC) and light-duty trucks(LT)[153]. In California, LDV segment alone contributed to 28% of state's total GHG emissions [3]. Plug-in hybrid electric vehicles(PHEVs) and battery electric vehicles (BEVs), collectively addressed as plug-in electric vehicles (PEVs), are being promoted at state and federal level to reduce LDV sector emissions and gasoline consumption[154]. Globally in 2019, cumulative PEV stock reached 7 million and new PEV sales exceeded 2.3 million[155, 156]. Nearly 315,000 new PEVs were sold in the U.S. in 2019 and 75% (234,000) were BEVs[156]. California is home to 47 % of nationwide PEV stock and leads the U.S. in PEV share (8%) of 2019 new car sales[157], but almost an eightfold growth within the coming decade[158] is required to reach its 2030 target of 5 million PEVs[40] .

Several demand-pull and supply-push strategies have been implemented to accelerate BEV adoption by mitigating barriers cost, range anxiety, charging infrastructure adequacy , and technology awareness barriers[159-161]. BEV and electric vehicle supply equipment(EVSE) purchase financial incentives, parking fee and high occupancy vehicle lane exemptions, free public charging, and preferential time-of use (TOU) charging rates, are some of the demand side incentive-based policies that correlated with BEV adoption[13, 106, 162]. Command and control technology forcing Zero Emission Vehicle (ZEV) mandate[5] policy, performance standards like the Low Carbon Fuel Standards (LCFS)[163], Corporate Average Fuel Economy/Consumption (CAFE/CAFC) targets and GHG standards[164] are considered to benefit BEV adoption though not as strongly as direct point-of-sale financial incentives[14]. The strength of association between BEV policies and market penetration may vary across geographies and demographics, but their direction is well documented and inferences are statistically probable[165]. The same cannot be posited if we expand the context beyond BEV market shares to their GHG mitigation potential, which is predicated upon their real-world usage patterns. BEV usage depends on the interactions between driving and charging behavior, technology attributes (range, vehicle specifications) and user preferences. In the policy domain, commonly used metrics for setting, standardizing, and monitoring GHG reduction targets are GHG/mile(gCO2e/mile) electric vehicle-miles traveled(eVMT) ,Utility Factor(UF). eVMT denotes the miles driven by off-board grid electricity and the role of electricity as a transportation fuel is expressed through the UF , which is the fraction of VMT electrified using off-board grid electricity.

A crucial aspect often overlooked in BEV GHG assessments is the household(HH) context. HH factors such as vehicle ownership, household size, and number of drivers, socioeconomics, and demographics, have consequential impacts on long-term purchase decisions, intra-day vehicle usage, and household travel demand[96]. BEVs have unique features that differs from ICEs which will influence how they are driven and charged. Depending on travel needs, individual preferences, operating costs, charging access and opportunities, vehicle miles traveled(VMT) by the BEV has cascading effects on VMT by other household vehicles. Roughly 45% of BEVs belong to two-car households according to an online survey of 15,000 PEV owners[81]. Contemporary studies offer a limited vehicle-centric perspective on BEV GHG impacts using self-reported trip diary information in stated preferences and choice experiment surveys of mainstream ICE , current, and prospective BEV users.

I quantify the GHG impacts of BEVs revealed from travel and recharging/refueling behavioral data of 73 ICE-BEV California households (73 ICEs, 30 Nissan Leaf, 21 Chevrolet Bolt, and 22 Tesla ModelS) observed over a year. Through scenario analysis, I further evaluate the effects of driving and charging behavior modifications and attribute upgrades on their prospective GHG abatement potential.

4.1.1 Household travel GHG constituents

Various mechanisms underpinning household travel GHG can be informed using the ASIF[166] identity which expresses GHG as the product of 4 variables: A(activity or VMT), S(mode share), energy intensity(I), and fuel (F) carbon intensities. Household travel emissions is the sum of ICE driving emissions from gasoline consumption and emissions due to electricity required for charging the BEVs. Household travel demand, share of ICE and BEV VMT, and energy intensities in gallons(kWh)/mile are susceptible household preferences, on-road conditions (congestion, grade, terrain), driving styles (urban, suburban, highway), vehicle characteristics (size, power, weight), and powertrain efficiencies [167, 168]. The quantity and quality of ICE miles (high energy intensity highway driving miles or comparatively low energy intensity cruising miles) substituted will directly impact the BEV energy consumption, volume of gasoline displaced, and thereby the HH GHG. If we include only the BEV, much of the insights on household travel demand and purpose of BEVs are lost. Furthermore, it is difficult to ascertain if there is any room for further abatement, compare across households and different BEV types to understand the relationships between travel needs, range, and GHG. These interrelationships highlight the need and the importance of household context in BEV GHG assessments.

4.1.2 Literature review

To assess BEV substitution and their GHG abatement potential, the first and the most critical information needed is their daily VMT and electrical energy required to accomplish their daily travel needs. In the absence of actual BEV usage data, daily VMT self-reported in trip diaries or collected via data loggers of mainstream ICE users are assumed to be indicative of typical daily driving patterns of BEVs[169-171]. Energy consumption is then calculated using the window sticker label and suitable charging scenarios are overlaid to estimate their charging needs by time of day, location, and charger level. In a Puget Sound Regional Council Traffic Choices data study[172], "BEV as second-car" concept is presented and suggests that a BEV with 60-mile range can electrify up to 55% of household travel and is acceptable to 90% of two-car households provided they tolerate the range inconvenience no more than three days per year and drive their other car[170].

A heuristic Household Activity Pattern Problem with Electric vehicle(HAPPE) model to randomly assign BEVs to 2-car households in the California Household Travel survey (CHTS)[173], reports that up to 54% of household travel can be electrified using a BEV with 80-mile range[174]. Trip diaries from household travel surveys and week to 2 month in-use data logged from conventional ICEs are analyzed to determine the BEV market viability in the Swedish and German LDV fleet and results indicate that the entire demand of the second car in 70% of all 2-car households can be met by a 138 mile range BEV, whereas a 244-mile BEVs is suitable to electrify the first car (the car that is used on higher number of days and accounts for a higher share of household travel)[169]. An optimization model is formulated using 1-3 months of granular GPS enabled logger data from 64 commuter households with 2-cars in Sweden, reinforces the notion suggested in a Seattle household study[175] that replacing the second car with a 91-105 mile range BEV is more favorable from days requiring adaptation and total cost of ownership(TCO) perspectives compared to the first car which requires 106-137-mile range[176]. By observing driving and charging behavior of retrofitted 100-mile range BMW Mini-E belonging to forty 2-car households in Berlin as part of large scale field trial , range utilization is discussed from a psychological perspective and results indicate that majority of the participants were comfortable in utilizing 77% of available range and prefer a safety buffer of 12%[177].

Average annual VMT of a Nissan Leaf (10,300 miles) and Tesla Model S (13,500 miles) BEVs is lower than that of conventional ICEs (14,600 miles) by 10% and 30% respectively based on automaker provided U.S. wide sample data[40]. Similar values calculated using information provided in the self-reported annual mileage and trip diaries of the 2017 National Household Travel Survey (NHTS)[178] noticeably underestimates the annual BEV VMT at 6,300 miles[179] . This illustrates short comings of relying on stated preferences or trip diary information that underestimate annual mileage and also progressively under-report long trips[22] (50/100/300-miles or more one-way), which is particularly important in the context of range-anxiety. The availability of real-world driving and charging data through U.S. wide demonstrations such as the Idaho National Laboratory (INL) EV project[180, 181], provided directly by the automakers for compliance and regulatory assessments in the U.S.[40], targeted short-duration data collections studies in major European BEV markets like Norway[182], Denmark and Sweden[183] has improved our understanding of BEV driving and charging patterns, and energy consumption , albeit GHG abatement potential of BEVs within the household travel demand context is ignored or inadequately addressed.

4.1.3 Research gaps

Prior research clearly advocates the need to have realistic representation of BEV usage to increase their usefulness to policymakers. Majority of studies irrespective of whether survey data or short duration logger data of ICEs or BEVs were used, primarily focus on the feasibility of a BEV to replace an ICE[171, 184, 185]. These studies present a diverse mix of quantitative and qualitative interpretation of days and miles a choice set of BEVs and associated attributes is unable to replace the ICE VMT. In studies that explicitly targeted 2-car households and monitor the BEV usage over few months duration, except for the improved granularity and the representativeness of the data compared to stated preference surveys, insights on relationship between range and household travel demand is found missing since only one type of BEV was used in short-duration field trials[169, 170, 174, 176, 186].

Within the contours of household travel demand, BEV substitution and GHG mitigation potential, I address the following research gaps:

- Quantifying BEV feasibility and substitution potential is necessary but not sufficient. It is important to articulate what these miles and days translate in GHG/mile.
- Most of the antecedents in literature ignore inter-household variability in the driving energy intensity which is directly reflected in per-mile energy consumption (Gallons/mile, kWh/mile) and emission factor differentials.
- Travel data collected from short-duration field trials and pilots may not be an adequate timeframe for the user to adapt and utilize the full BEV range. Observing actual usage for a year captures the full spectrum of trips and VMT.
- Heterogeneity in BEV attributes like range and specifications is scarce in previous observational BEV usage studies. This precludes cross-household comparisons among BEVs with comparable range but disparate specifications, drivetrain architecture, and efficiencies.

4.1.4 Study objectives

I present a unified framework to quantify the substitution and well-to-wheel (WtW) emission abatement potential of BEVs at the household level. I utilize a highly resolved yearlong travel and charging dataset collected via on-board diagnostic port (OBD) data loggers of 146 vehicles (73 ICEs, 30 Nissan Leaf, 21 Chevrolet Bolt, and 22 Tesla Model S) from 73 two-car ICE-BEV California households. I selected six scenarios to capture the individual and combined effects of travel day vehicle selection and overnight full charging depending on whether the household retained its current BEV attributes or replaced it with a longer-range efficiency or longer-range sportier performance-oriented BEV.

4.2 Data and Methods

The primary source of data is from the Advanced Plug-in Electric Vehicle Travel and Charging behavior[28, 29]. This project was started in 2015 to understand how current PEVs being used a day-to-day basis within the context of household travel in California. This study included an online survey followed by a yearlong data collection study of a sub-sample of respondents. Data loggers were installed in all the vehicles in this sub-sample of households who expressed interest in participating in the logger study and planned to keep their PEV for at least a year. Details about the online survey, survey administration, and comparisons of select indicators observed in this study with California statistics[17, 82, 84, 178, 187] and prior literature are detailed in the **Appendix C**.

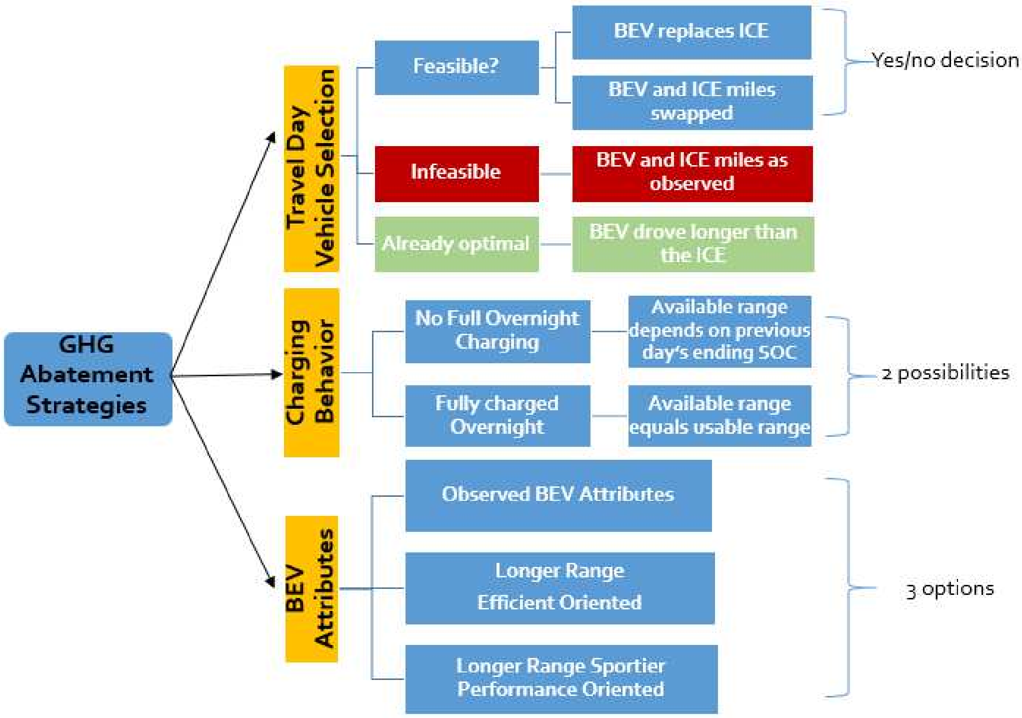
Table 4.1. Average annual driving and charging summaries

		Battery Electric Vehicle (BEV)			**Internal Combustion Engine Vehicle (ICE)**				**Household (HH)**	
BEV type	*N HH*	*eTrips*	*eVMT*		*gTrips*	*gVMT*	*Gasoline*		*HH Trips*	*HH VMT*
Leaf	30	1382	10841		1089	9258	386		2471	20099
Bolt	21	1303	12470		945	9625	367		2248	22095
T60	12	952	17236		1097	7356	388		2049	24592
T80	10	866	13507		902	6213	308		1768	19720
Total	**73**	**88899**	**929795**		**74700**	**631126**	**27040**		**163599**	**156091**
	Number of charging sessions by charger type[90, 188, 189]				**Charged energy by charger type (kWh)**				**Average charging session duration (minutes)**	
BEV type	*All levels*	*L1/L2*	*DCFC*		*All levels*	*L1/L2*	*DCFC*		*L1/L2*	*DCFC*
Leaf	296	246	50		2455	1784	659		277	26
Bolt	291	283	8		3374	3235	134		285	49
T60	273	238	35		6345	5363	905		250	36
T80	236	219	17		5121	4539	528		194	33
Total	**20637**	**18400**	**2237**		**271852**	**231194**	**38731**			

prefix e and g denote electricity and gasoline ; total refers to the entire dataset ; all distances driven, electrical energy and gasoline consumed are in miles, kWh, and gallons respectively.
Level 1 (L1) charger is rated 120VAC , 12-16A ; Level 2 (L2) charger is rated 208-240VAC, up to 80A; Direct Current Fast Charger(DCFC) is rated 200-500VDC, up to 350A. Tesla Model S BEVs with 60-80kWh and more than 80kWh usable battery capacity are categorized as T60 and T80 respectively for notational simplicity.
Descriptive statistics on HH VMT allocation by driving distances and speeds and share of HH VMT by travel day usage patterns and its contribution to overall HH GHG are presented in the Supporting Information.

4.2.1 Logger data

In the sub-sample of 73 households, Fleet Carma C2 or C5 data loggers[85] were installed in the on-board diagnostic port of all vehicles belonging to the household (146 vehicles in total). These data loggers monitor and collect data at very high resolutions (1Hz to 10 Hz) which facilitates binning the ICE and BEV distance driven by three distinct energy intensities indicative of three driving styles : city or urban driving (0-45mph], mixed or suburban (45-60 mph] and highway driving styles (60mph or more). This accounts for inter household variability in driving energy intensity, an approach is entirely missing in all contemporary BEV usage studies, observational or otherwise. I do not use average trip speeds to associate a specific driving style to an entire trip, but rather break down the distance driven in every trip by speeds at 5 mph intervals and subsequently bin them as city, mixed or highway styles. Other important variables logged included but not limited to : date and time stamps, trip/charging session starting and ending battery state of charge (SOC), AC and DC currents and voltages, gasoline consumed, electrical energy consumed (discharged while driving), produced (due to regenerative braking), and charged, charger level, and trip distances. Table 4.1 summarizes the average annualized household trips, miles, fuel and electricity consumption by source (ICE or BEV). The aggregate annualized data for this is study includes 164,000 household trips (89,000 BEV etrips and 75,000 ICE gtrips), 1.56 million household VMT (930,000 eVMT by the BEV and 630,000 gVMT by the ICE), spanning 25,000 days, consuming 27,040 gallons of gasoline, and 272 MWh of electricity. On average every household was monitored for 325-374 days depending on the BEV type.



Scenario Name	Travel Day Vehicle Selection ("select")	Charging Behavior ("fullchg")	BEV Attributes
	BEV swap replace/allowed?	*Overnight fully charged?*	*Observed or upgraded?*
S1 Obs	Yes, if feasible	No	Observed attributes
S2 Obs FullChg		Yes	
S3 LREffi		No	Longer-range (238-mile) and efficiency oriented
S4 LREffi FullChg		Yes	
S5 LRPerf		No	Longer-range (275-mile) and sportier performance oriented
S6 LRPerf FullChg		Yes	
Obs_Beh	Observed BEV attributes, vehicle selection, and charging behavior (Baseline/Reference)		

Figure 4.1. Methodological framework, GHG abatement strategies, scenario selection and nomenclature.

4.2.2 Methodological framework for GHG abatement and scenario selection.

I considered three GHG mitigation strategies – travel day vehicle selection, overnight fully charging behavior, and BEV attributes, Figure 4.1. Each of these strategies when combined, lends itself to a total of 6 scenarios:

Obs_Beh: Reference scenario. Observed driving and charging behavior, and travel day vehicle selection. The available range is calculated by scaling the usable range proportionally to previous day's ending state of charge (SOC) .

S1 Obs Select: I assume that at the beginning of a given travel day, users select the BEV instead of the ICE whenever feasible, i.e. range is sufficient to accomplish the ICE gVMT. The available range at the start of travel day is proportional to the previous day's ending state of charge (SOC) observed. Households keep their current BEV attributes.

S2 Obs Select FullChg: S1 Obs Select plus BEVs fully charge overnight at home. The available range at the starting of travel day is their full usable range.

S3 Select LREffi/S4 Select LREffi FullChg: Follows S1 Obs Select/S2 Obs Select FullChg. Households upgrade to a longer-range efficiency-oriented BEV.

S5 Select LRPerf/S6 Select LRPerf FullChg: Follows S1 Obs Select/S2 Obs Select FullChg. Households upgrade to a longer-range sportier performance-oriented BEV.

I selected three strategies–Travel day vehicle selection, full overnight charging, and BEV attribute upgrade. Travel day vehicle selection as the name implies is among the choice set of vehicles available (ICE and/or BEV), what vehicle was chosen and how much distance was driven using the specific vehicle type. Referring to Table C-1 of the **Appendix C**, in this dataset more than two-thirds of the households have 2 or more drivers so on a given travel day, either one (ICE or BEV) or both the vehicles could be used depending on the household travel demand. Household travel demand on a given day which is the sum of VMT by the BEV and ICE, and the BEV range together influence which vehicle was chosen and the corresponding miles driven. The key determinants of the household GHG are the absolute miles and the carbon intensity of miles. GHG reduction is ensued by : i) selecting the BEV and shifting the ICE miles to the BEV on days only when the ICE was driven ; and ii) allocate ICE miles to the BEV and vice versa on days when both vehicles were driven and the ICE drove longer than the BEV. Travel day vehicle selection strategy thus captures shifting high carbon intensity gVMT to low carbon intensity eVMT whenever feasible. Feasibility here means that the BEV has enough range to accomplish the ICE gVMT at the same energy intensity levels. Referring to Figure 1 of the manuscript, on days when the BEV does not have enough range to replace or swap the ICE miles is classified as infeasible and the GHG as a result of these days is called hard to abate or unabatable GHG. Already optimal refers to the days when users made the right travel day vehicle selection that contributes to minimal GHG. Days when only the BEV was driven, or BEV drove longer than the ICE are instances where additional GHG mitigation is not possible.

If the battery state of charge (SOC) is 100% (fully charged) then the available range and usable or maximum possible range are identical. Under-utilization of the BEV range occurs if the travel day starting battery SOC is less than 100%. The difference between usable range and available range at the beginning of the travel day depends on the overnight charging behavior. I wanted to study if everybody charged to full capacity overnight every day are the BEVs substituting more ICE miles compared to not fully charging overnight. This is of topical interest and concern to policymakers from the point of incentivizing home charging infrastructure through direct subsidies and encouraging home charger utilization when electricity prices are cheaper by designing charging rates by time of use (TOU) . The charging behavior strategy is an insight into what would happen if all these BEV users charge overnight once their previous day's mission profile ended and thereby eliminating any possibility of range under-utilization. An immediate consequence of this is the marginal positive effect on the number of days the BEV can be used instead of the ICE, irrespective of whether only the ICE or both ICE and BEV was driven.

The third important GHG mitigation strategy I consider is what would happen if the attributes of the BEV (range and specifications) was retained or upgraded. I considered three specific situations: i) households keep their existing BEV as it is ; ii) households decide to replace their existing BEV and upgrade to a longer-range efficient oriented BEV ; and iii) households decide to replace their existing BEV and upgrade to a longer-range sportier performance oriented BEV. In the following sub-section using the framework for GHG mitigation as discussed above, I elaborate on the scenario selection.

4.2.3 Other Parametric assumptions and caveats

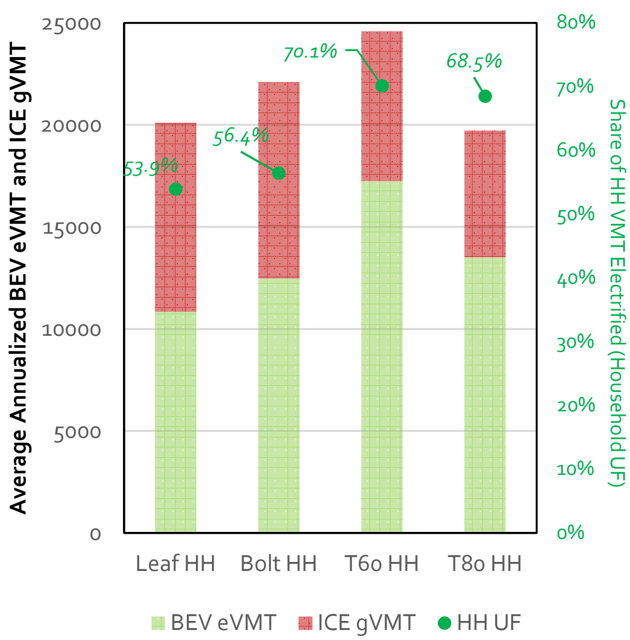
In this chapter, I use an all -or nothing substitution between BEV and ICE miles on days when there is sufficient battery capacity available for the BEV to replace or swap ICE miles. This perfect foresight in of travel day VMT is acceptable considering that irrespective of which vehicle(s) were driven, their daily travel needs will be met. Since actual usage and VMT by both vehicles is monitored , any short-run elasticities with respect to prices , traffic, climate, respondent socio-economic and demographic indicator is explicitly measured in their actual VMT change. There is a general consensus among researchers on the importance of choosing a Cradle-to-grave (C2G) or WtW approach to account for the embodied GHG in battery manufacturing and explicitly acknowledging the sensitivity of BEV GHG assessments to regional diversity in electricity generation mix and ambient conditions[167, 168, 190-194]. Since we are strictly dealing with California sample, I used state-wide WtW emission factors[195, 196] for gasoline(11405.85 gCO2e/gallon) and electricity (378.54 gCO2e/kWh).

Sample size and generalizability limitations are intrinsic and unavoidable as with any study that analyze real-world operation[10, 18, 54, 80],. The characteristics of survey respondents in this study followed general assumptions about BEV early adopter traits such as higher income and education levels, higher share of PEV owners living in detached or townhouses compared to general population[30]. Despite the small sample size of vehicles, the BEV make and models considered in this study accounted for 73% of all rebates issued to BEVs between 2015 and 2020 under the California Clean Vehicle Rebate Project[7].

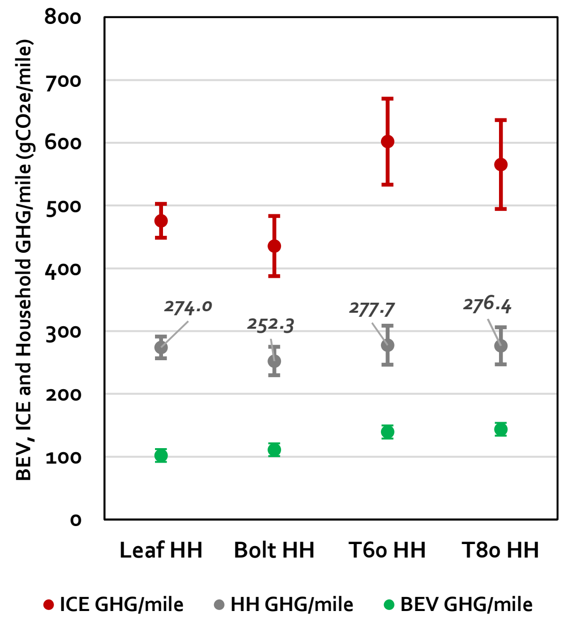
4.3 Results

I summarize select insights from observed behavior followed by the scenario specific implications on BEV substitution and GHG abatement potential.

4.3.1 Observed behavior UF and GHG



(a)

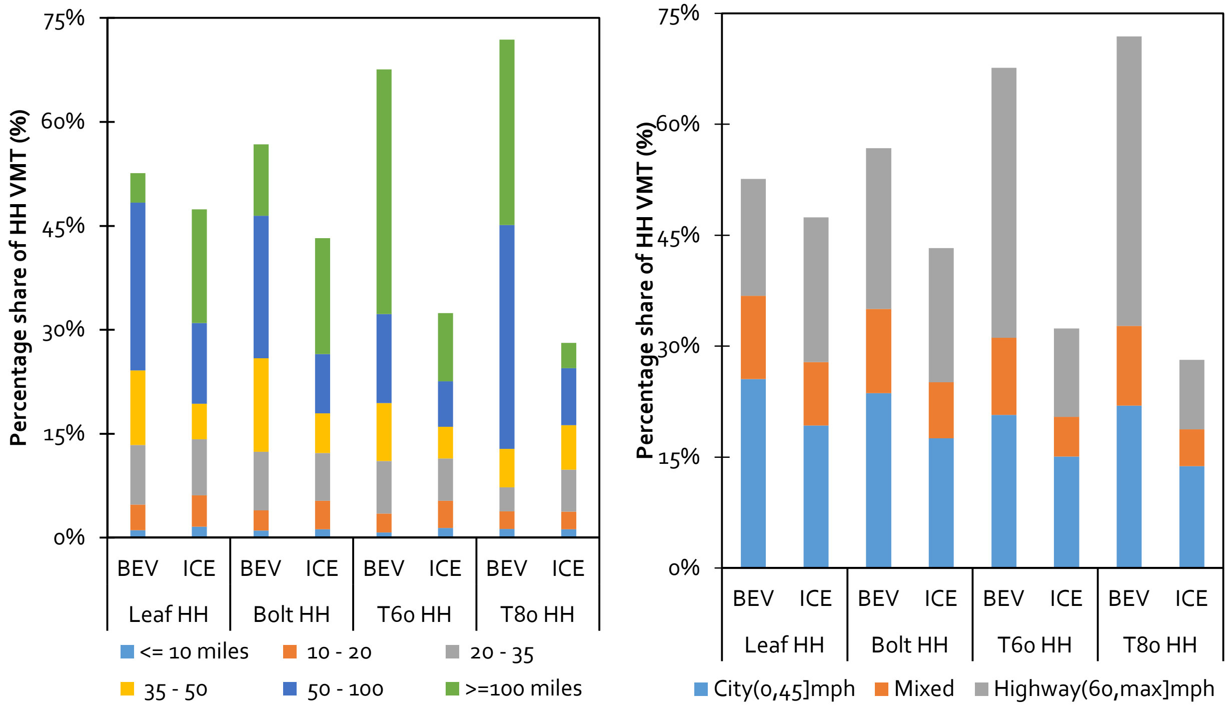


(b)

Figure 4.2**.** Average annualized eVMT, gVMT, UF, and GHG observed.

(a)Average annual miles driven and the UF is shown on the secondary Y-axis ; (b) Per-mile WtW GHG emissions by vehicle type and for the household. The household GHG is normalized to the household VMT. Utility Factor (UF) is the share of household VMT electrified – ratio of BEV eVMT to total HH VMT and is shown in percentage (%).

Figure 4.2 captures the relationship between average annualized mileage, UF, and GHG. Overall, Bolt households have the lowest GHG per mile and their UF is only slightly more than that of the Leaf HH UF despite the Bolts having more usable range (238-miles) than Leaf (87-miles). **Figure 4.2** shows that the effect of increasing range and the resulting UF gains not necessarily translates into GHG benefits and potential trade-offs are involved. The T80 (235-mile) has more range than the T60 (205-mile) and comparable range as the Bolt. However, T60 can electrify highest share of HH VMT but it has the highest HH GHG. ICEs on average in the Tesla HHs (T60 and T80) are inefficient compared to the ICEs in Bolt or Leaf HHs. The above instances illustrate how our inferences could vary depending on the metric (UF or GHG) and level of disaggregation(BEV only or household level).



(a) (b)

Figure 4.3. Observed HH VMT allocation by vehicle used. (a) by driving distances ; (b) by driving speeds

Figure 4.3 depicts share of HH VMT allocated between the BEV and ICE binned by daily VMT and driving speeds . The percentage share of VMT by vehicle type in Leaf and Bolt HHs are comparable though Bolt's usable range (238-miles) is more than double the usable range of a Leaf (87-milesFigure 4.3(a) shows that ICEs are preferred over the BEVs in Leaf and Bolt HHs for traveling 100 miles or more but the Teslas (T60 and T80) were used for majority of daily travel 100 miles or more. It is interesting to note that the Bolt HH VMT allocation between the BEV and ICE is more aligned towards the Leaf rather than the T60 or T80. These trends are also reflected if we look at the HH VMT allocation by vehicle type and driving speeds binned into city, mixed or highway driving styles in Figure 4.3(b).The average usable range of Bolt (238-miles) is more than the average usable range of T60 (205-miles) in this dataset(Figure S3). However, the proportional allocation of HH VMT between the ICE and the Bolt/T60 binned by daily distances driven and driving speeds diverge noticeably.

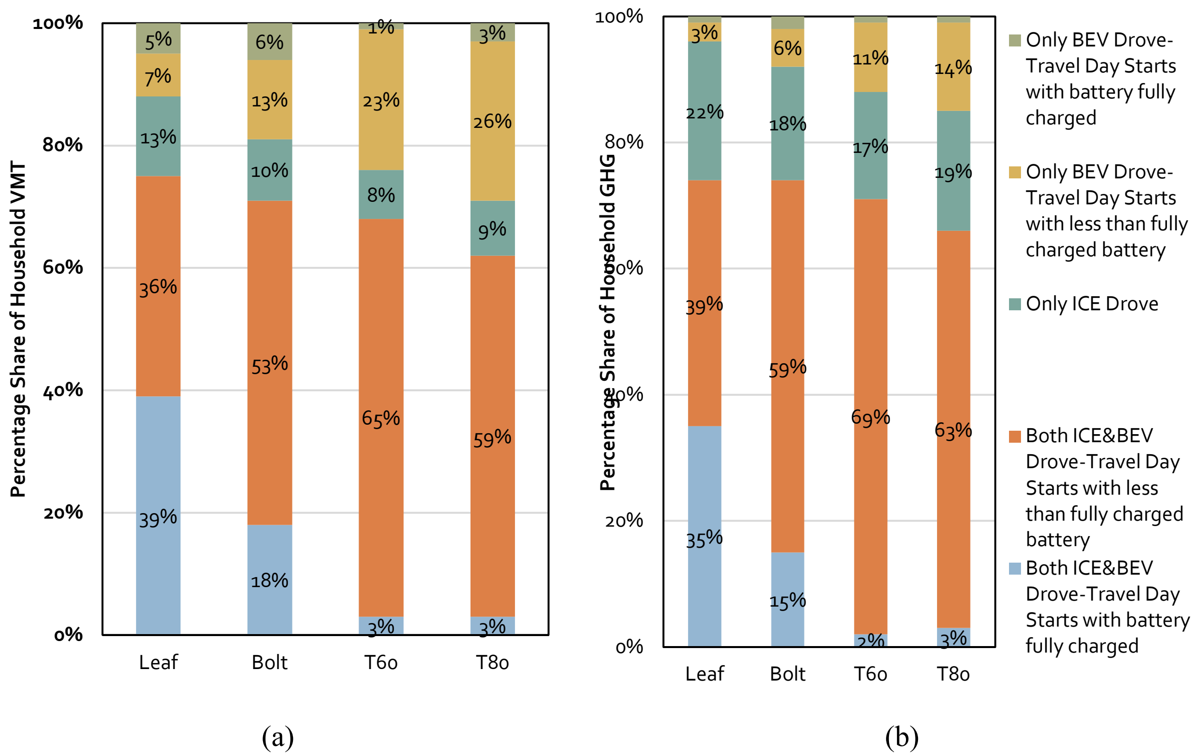


Figure 4.4 Observed HH VMT allocation and GHG contribution by type and number of vehicles used, and travel day starting SOC of the BEV. (a)Observed HH VMT allocation and ; (b) contribution to HH GHG. The type of day was chosen to be along the same lines as the scenarios.

Figure 4.4 captures the relationship between HH VMT and what it portends for the HH GHG if we disaggregate the travel day based on the number of vehicle(s) driven and the travel day starting SOC of the battery. It is not surprising that majority (60-75%) of the HH VMT and GHG is due to both vehicles being driven. However, nearly 9-13 % of HH VMT using the ICE alone causes nearly 20% of household GHG on average across all BEV types. At-least 4-15% of HH GHG (corresponding to ~12-30% of HH VMT) is optimal as is and further GHG mitigation is not possible because only the BEV was driven. With increase in range, the number of days and thereby the share of HH VMT by the BEV alone also increases from 7% in the case of Leaf HH to almost 25% in the case of T80 HHs.

4.3.2 Substitution potential of BEVs under different scenarios

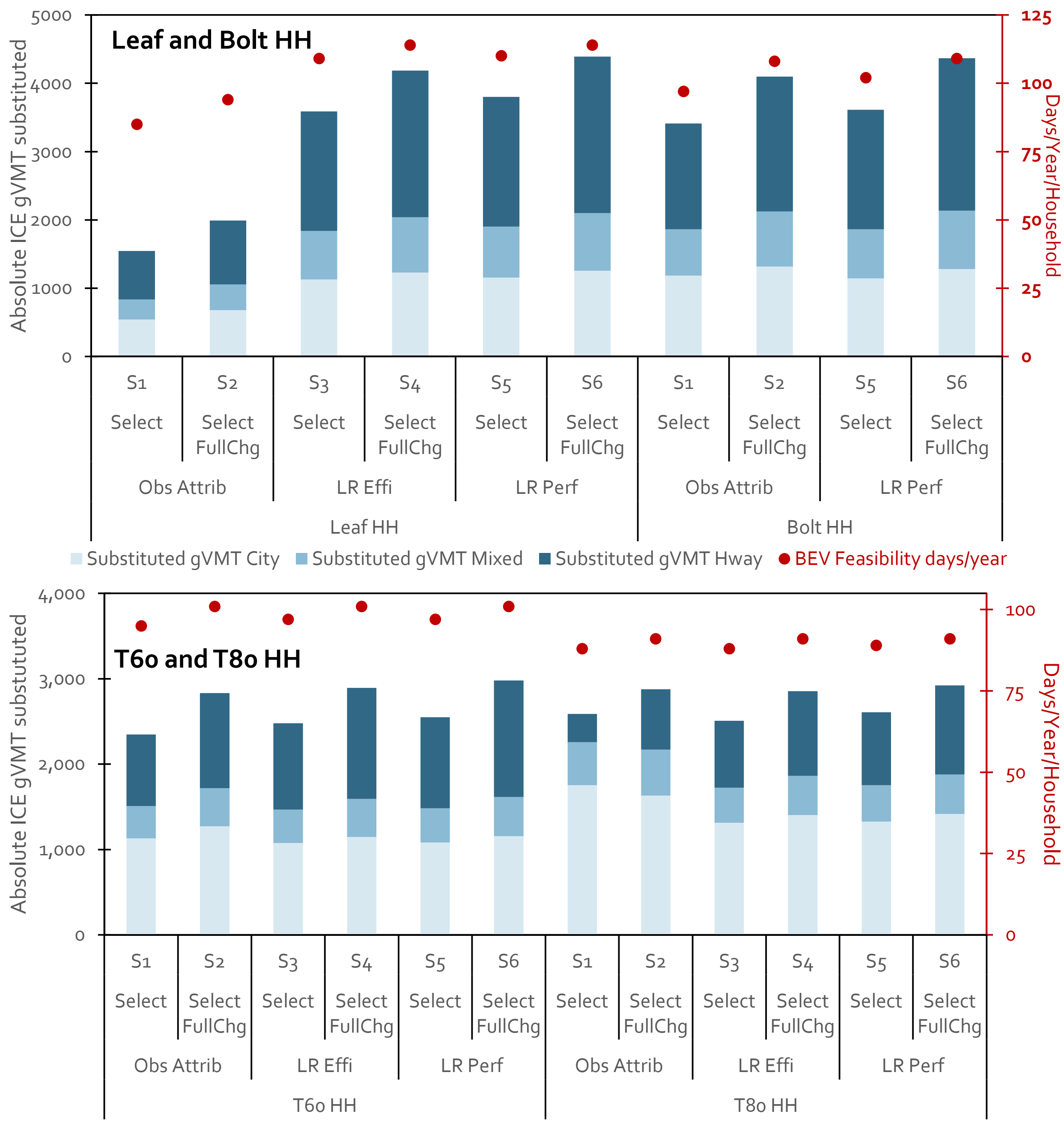


Figure 4.5. ICE gVMT substituted by driving style(primary Y-axis) and BEV feasibility in days/year/household (secondary Y axis).

Figure 4.5 depicts the average annual number of days per household feasible for the BEV to replace the ICE, and the resulting ICE gVMT substituted by driving style. Scenario analysis indicated it is feasible for the BEV to replace the ICE on 85-97 days/year and substitute 1544-3409 ICE gVMT/year by adopting the travel day vehicle selection strategy alone. By fully charging the BEVs overnight (*S2*) , feasibility and substitution potential increases to 90-108 days/year and 1993-4390 miles/year. Tesla HHs (T60 and T80) saw only slight improvements in the substitution potential if they are upgraded to a longer-range efficiency oriented BEV or longer-range sportier performance oriented BEV. It is interesting to note how the observed user preferences manifests in the magnitude and type of ICE miles substituted. Excluding the BEV attribute upgrade scenarios, the average daily ICE gVMT substituted is close to 20 miles in a Leaf HH. It increases to 25-30 miles in a Tesla HH (T60 and T80) and was highest in the Bolt HH (35 miles roughly). The energy intensity of ICE miles substituted markedly differed between the Tesla (T60 and T80) HHs and the Leaf and Bolt HHs. Nearly 50% (1132 out of 2348 miles) and 68% (1752 out of 2589 miles) of ICE miles substituted by the T60 and T80 respectively were of city driving type. In stark contrast, almost half of the ICE miles substituted by the Leaf (710 out of 1544 miles) and Bolt (1546 out of 3409 miles) were of highway driving style. These inferences accentuate the household context which provides a deeper insight into driving and charging preferences, which influences GHG benefits of BEVs.

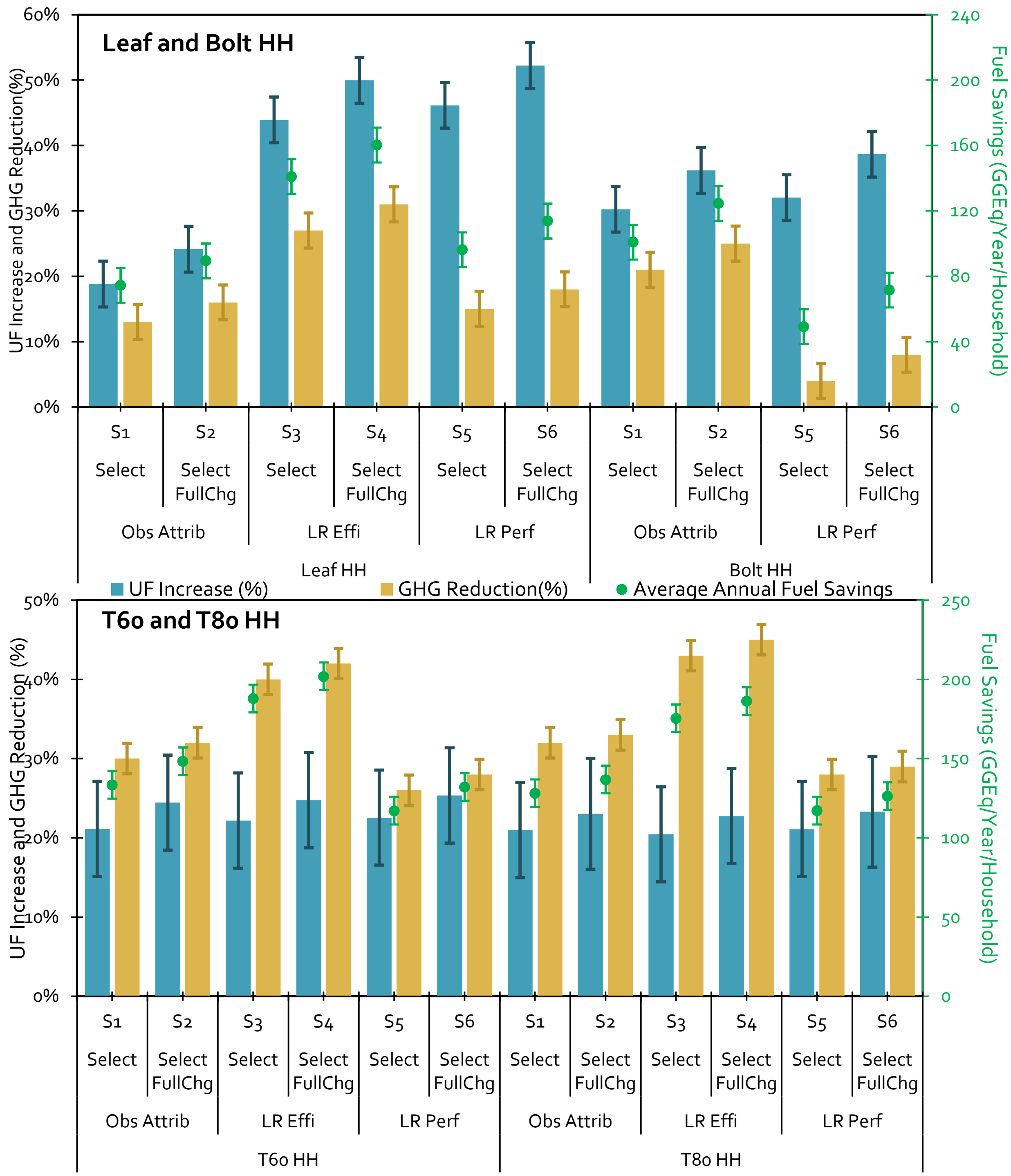


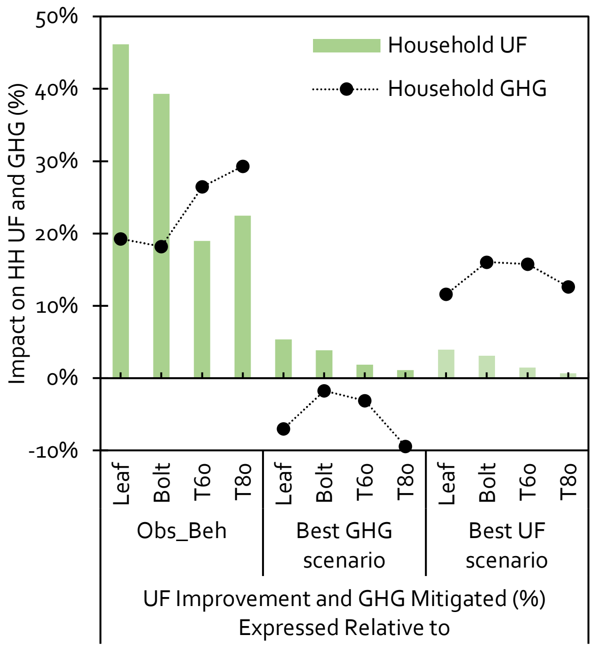
Figure 4.6. Percentage change in household UF and GHG (primary Y-axis) and average annual fuel savings in GGEq (secondary Y-axis) relative to *Obs_Beh*. 33.7 kWh/Gallon gasoline equivalent[197].

4.3.3 Overall impact on household utility factors , GHG abatement, and fuel savings

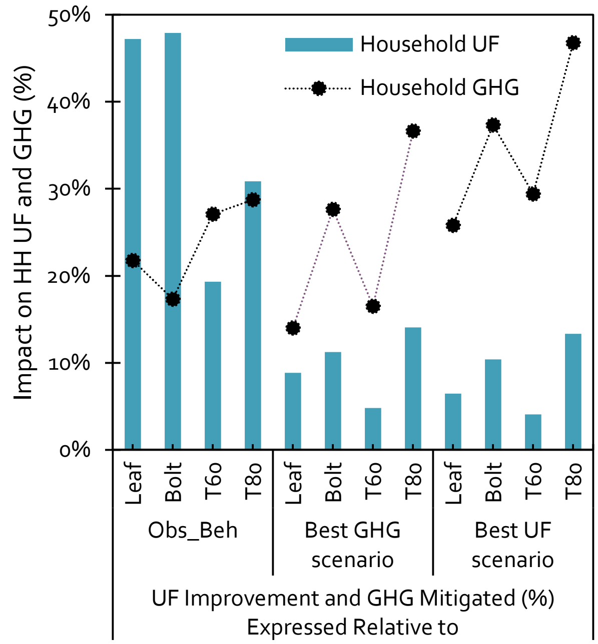
Impact of different GHG abatement strategies on UF, GHG, and fuel savings relative to *Obs_Beh* is show in Figure 4.6. The UF increased on average by 20% for the Leaf and Tesla (T60 and T80) HHs, and 30% for the Bolt HH under the travel day vehicle selection strategy(*S1)*. By fully charging overnight (*S2*), an additional improvement of 2-6% is possible. Leaf HHs can electrify on average 45-50% more miles relative to *Obs_Beh* by upgrading to a longer-range efficiency (*S3 and S4)* or sportier performance oriented BEV (*S5 and S6).* Bolt HH UF slightly improves by upgrading to longer-range sportier performance oriented BEV in *S5 and S6* scenarios compared to *S1 and S2* scenarios.

On average 12-16% of Leaf HH GHG can be reduced relative to *Obs_Beh* by travel day vehicle selection (*S1*) and full overnight charging behavior strategy (*S2*). These improvements almost doubled to 27-31% if the Leaf was upgraded to a longer-range efficient oriented BEV(*S3 and S4).* However, if the attribute upgraded was a longer-range sportier performance oriented BEV *(S5 and S6)*, only 15-18% of GHG abatement is possible even though it electrifies 45-50% more miles relative to *Obs_Beh.* Nearly 20% of Bolt HH GHG can be mitigated through travel day vehicle selection and an additional 5% is possible by fully overnight charging strategy. By upgrading to a longer-range sportier performance oriented BEV, 30-40% improvement in Bolt HH UF (*S5 and S6*) translates into only 4-8% HH GHG abated relative to *Obs_Beh*. It is interesting to note that the HH GHG abatement potential is roughly 26-28% if the Tesla HH (T60 and T80) upgraded to a longer-range sportier performance oriented BEV, about 4% less than what they could achieve by retaining their current BEV attributes and adopting the travel day vehicle selection strategy.

Relative to *Obs_beh*, on average across all scenarios and BEV types varying levels of fuel savings can be realized. However, UF improvements could come at the expense of an overall increase fuel consumption (GGEq). Compared to *Obs*_Beh, a leaf HH could save 141-160 GGEq/year and electrify 44-50% more miles by upgrading to a longer-range efficiency oriented BEV. This fuel savings reduces by nearly 30% to 96-114 GGEq/year if the upgraded BEV attribute is a longer-range sportier performance oriented BEV even though its UF improvement relative to *Obs_Beh* is comparable(46-52%). Bolt HHs nullify 40-50% fuel savings (101-125 GGEq/year) achieved using their current BEV attributes and adopting the travel day vehicle selection and full overnight charging behavior by upgrading to a longer-range performance oriented BEV (49-72 GGEq/year savings relative to Obs_Beh).



(a) 400-mile BEV assigned to all 73 HHs



(b) 400-mile BEV assigned to sub-sample of 38 HHs

Figure 4.7. Effect of upgrading to 400-mile BEV on UF and GHG. Percentage change in UF and GHG expressed relative to observed behavior, best GHG and best UF scenarios. (a) Entire sample of 73 HHs upgrade to 400-mile BEV; (b) Sub-sample of 38 HHs upgrade to 400-mile BEV.

4.3.4 *Deeper GHG reductions and future BEV attributes*

Observed behavior and scenario specific outcomes on UF and GHG discussed thus far are based on *ex-post* availability of BEV make, model, and specifications. To ascertain the UF and GHG prospects of advanced BEV designs, I assume all households upgrade to a 400-mile BEV, analogous to a just introduced Tesla Model S Long-range Plus[198]. I find that relative to *Obs_Beh*, UF and GHG improves by 20-50% and 20-30% respectively, **Figure 4.7(a).** Their impact relative to the best UF and best GHG scenario, are comparatively smaller and could even be detrimental. UF increases by only 1-4% relative to the best UF scenario, and GHG could worsen by 2-9% relative to the best GHG scenario.

Considering the effect of long distance travel needs on range anxiety, BEV purchase decision, usage patterns, and VMT allocation within the household[199, 200], I performed additional analysis to identify infrequent ICE gVMT that the BEV cannot substitute and the resulting GHG that is hard to abate. Analysis indicated that the source of hard to abate GHG is attributable to a total of 175 days of travel from 38 HHs (17 Leaf, 11 Bolt, 7 T60, and 3 T80 HHs). The average ICE gVMT on these days was 306 miles twenty-nine of the 38 ICEs in these HHs are LT. Within the sub-sample of 38 HHs, UF and GHG benefits of a 400-mile BEV relative to the best UF and GHG scenario was highest in T80 HH, followed by the Bolt HH, T60 HH, and Leaf HH stand to gain the least, **Figure 4.7(b).** Conventional wisdom purports increasing the range can mitigate BEV adoption barriers , increase their usage, and thereby their GHG benefits[201, 202]. These observations demonstrate that range alone cannot be a reliable proxy to project GHG benefits of more and future BEV designs and trade-offs exist between different policy goals.

4.4 Discussion

The BEV market is expected to grow in the upcoming decades with many state, regional, and national governments tightening emission standards and implementing a suite of supply side technology forcing and demand side incentive policies to increase their penetration. Cost, range anxiety, and charging infrastructure accessibility barriers alongside user preferences and subjective valuation of BEVs in fulfilling their travel demand poses difficulties in examining their real-world GHG benefits. Insights gleaned from current works on BEV usage and their GHG abatement potential depend on type of survey (cross-sectional or longitudinal surveys), methodology (stated or revealed preferences), data acquisition method (online, mail, phone, in-person, data loggers), duration of study and spatiotemporal resolution of data, sample population (mainstream ICE users, current or prospective PEV buyers), geographical coverage, level of disaggregation (vehicle or household level), and system boundary for GHG quantification. It is important to frame and appraise GHG benefits of BEVs in a manner that reflects the current landscape of consumer awareness, purchase decisions, BEV attribute perception, and driving and charging preferences. Studying BEV usage in isolation could lead to inaccurate estimates of their GHG benefits since majority of BEVs belong to multi-car households. This highlights the importance of gauging the environmental performance of BEVs from a household vehicle portfolio perspective that included vehicle substitution patterns by daily distances and driving styles, efficiency, and emission factor differentials of both BEVs and ICEs. As a step in this direction this study quantified the substitution and GHG abatement potential of BEVs using real-world observational data of 73 ICE-BEV California households.

California sample of BEV households observed in this study are making sub-optimal decisions regarding their travel day vehicle selection , overnight charging behavior, and consequently their usable range from the perspective of GHG abatement. These are attributable to interlinkages between vehicle specifications and features (BEV and ICE) , driving and charging behavior, and household preferences Household preferences are reflected across different timescales– travel day vehicle selection and VMT allocation; overnight charging behavior ; trip level driving styles ; perception, valuation, and alignment of BEV attributes with typical travel needs ; frequency, duration, and intensity of atypical travel needs ; and long-term purchase decisions. The underlying interactions between household preferences , and the choice set of abatement strategies can lead to diverse outcomes depending on the policy goal and the level of disaggregation (BEV only or household level). Policy makers need to continually fine tune existing incentives (financial and/or non-financial) or introduce new incentives to encourage not just the adoption but also the utilization of BEVs to maximize their GHG benefits. In this regard , information about real-world BEV usage is extremely valuable for policy makers as it will offer insights into the current barriers and opportunities to better inform future policies. Understanding daily driving needs and how different market segments perceive and value BEV attributes is crucial for auto manufactures for optimal BEV design and model offerings. UF and GHG impacts of state-of-art 400-mile BEV presented in this study indicates that real-world implications of future BEVs are vulnerable to subjective and diversified user needs and how well it is aligned with BEV attributes. Use cases and role of BEVs in meeting household travel demand could be dictated by their features other than just the range. Magnitude and direction of differences between other BEV GHG assessments and results presented in this study can also help researchers in parametric updates, calibration and validation efforts to strengthen the representativeness or correct for the lack thereof in vehicle choice modeling[203], powertrain simulation tools[204], and integrated assessment studies[205].

5 Conclusions

Contemporary studies on PEV usage rely on assumptions about their driving and refueling behavior using data from stated preferences of potential PEV owners or reported behavior of PEV early adopters, or household travel survey trip diaries of ICE vehicle drivers. These assumptions have widespread ramifications on the energy and emission estimates of PEVs embodied in existing policies. This dissertation utilized observational data and highlighted its implications on three PEV topics. The first chapter developed an analytical procedure to systematically quantify what aspects of observed driving and charging behavior contributes to PHEV utility factors diverging from sticker label estimates. The second chapter delved deeper into short-range and longer-range PHEVs and identified distinguishing driving and charging preferences that have the most positive and negative influence on their electrification potential. The third chapter examined the current and prospective GHG benefits of BEVs in two-car households using scenario analysis to capture one or combination of travel day vehicle selection, overnight charging behavior, and BEV attribute upgrades.

A common theme that cuts across these chapters is that the California sample of PEVs charge less frequently and drive more aggressively than the conventional wisdom embedded in standardized test cycles which often serve as benchmarks for policymakers and OEMs. Chapter 2 showed that perverse incentive exists especially for short-range PHEVs (20-miles or less) when they don't charge at all and use their PHEV like a regular HEV nearly 20-30% of the time. On the other hand, range-underutilization is was noticed in the case of second generation 53-mile Chevrolet Volt. These examples are illustrative of self-selection bias among potential PHEV buyers wherein users who are less likely to charge or do not have home charger access buying short-range PHEVs. In addition, potential PHEV buyers over or underestimating their typical daily travel needs which is out of alignment with the charge depleting range capabilities. Future PHEV policies could investigate the suitability of alternative performance metric such as eVMT instead of UF while designing the incentive structure.

Household travel electrifications and emissions were investigated in Chapter 4. Results indicated that the potential tradeoffs exist between increasing share of household travel electrified and reducing household GHG. Inclusion of the household context reinforces the value and the need for examining the environmental performance of BEVs in relation to the other car. Baseline observed behavior revealed that 25-30% of household GHG can be reduced if users select their BEV instead of the ICE. Results of the scenario analysis indicated that miles substituted by the BEV when comprehended alongside the efficiency and emission factor differentials of both BEVs and ICEs yields two distinct pathways depending on the chosen policy goal. For household GHG mitigation, longer range efficiency oriented BEV are suited whereas a longer range sportier performance oriented BEV electrifies highest share of household travel. The presence of a larger footprint ICE plays a role in the hard to abate GHG alluding to the necessity of future PEV policies and OEM model offerings to focus on electrifying larger platform cars.

The broader impacts of this research are:

- Provides a realistic assessment of PEV emissions and energy consumption.
- Helps policymakers in determining the most effective policies and strategies to encourage PEV usage and understand their true emission benefits.
- Improves our understanding of how different market segments value different PEV technologies in meeting their travel needs
- Facilitate discussions on how insights gathered from PEV experience today can better inform their future policy needs and potential impacts.

5.1 Future Research Directions

Chapter 2 quantified real-world UF differences from window sticker label/SAE J2841 estimates and the relative contributions to these deviations attributable to observed driving and charging behavior of PHEVs. Since PEV policies are integrated within the broader fuel economy and emission standards in the form of offsets and credit multipliers, better understanding of UF estimates is valuable in the calibration and regulatory assessments of PHEVs. Replicating the procedure developed in Chapter 2 to other and more recent PHEV models and incorporating a life-cycle approach is worth investigating further. More specifically, observed deviations could be parameterized in sensitivity analysis of life-cycle emissions , total cost of ownership , and cost parity studies. At an elemental level, SAE J2841 finds its application in type approval and credit allocation in European and Japanese fuel economy standards, and China's stage VI LDV emission standards. Applying the analytical procedure outlined in Chapter 2 to such regions and scrutinizing the policy implications would be of resourceful and of timely value to the broader scientific community interested in improving the accuracy of UF assessments.

Chapter 3 addressed charging accessibility by location (home, away, home and away) and utilization (frequency of charging, duration of charging session). Results indicated that home charging frequency has the largest positive effect on the eVMT by long-range PHEVs (30 miles or more), whereas eVMT by short-range PHEVs (20 miles or less) increases by facilitating charging at home and away locations. The above circumstance presents a classic conundrum for policy makers in determining whether incentivizing longer-range PHEVs or investing in public charging infrastructure expansion can enable create more eVMT. As the market share of PEVs belonging to multi-unit dwelling and apartment complexes increase, role of public charging infrastructure becomes even more important. A more granular approach expanding upon Chapter 3 that includes spatio-temporal aspects of charging to identify trip level variables that affect decision to charge or not charge, identify missed charging opportunities at public charging locations, and its implications on the net environmental impact (driving and charging) and electrification potential of PHEVs definitely merits a deeper analysis.

Household level implications of PEV technologies is an unexplored research topic which can lend itself to several future research inquiries of tangible and immediate relevance to policymakers and automakers. In Chapter 4, I examined how the level of disaggregation (vehicle or household level) and the metric (UF or GHG) manifests in quantifying the net environmental impact of BEVs in 2-car California households. Scenario selection were based on the BEV alone and it will be valuable to consider scenarios that capture household fleet turnover and identifying optimal portfolio of household vehicles for maximal GHG benefits. The foundational aspects of the scenario analysis can readily be expanded to evaluate the impacts of cross-technology and cross-vehicle attribute substitutions. For example, replacing the BEV with a PHEV and or replacing the ICE with a PHEV. The expanded framework can be applied to the case of 2-car ICE-PHEV households whilst including ICE fuel economy standards. These research areas are very important in future household travel emission mitigation studies.

Appendix A

Supporting Information for Chapter 2

Exponential and fit coefficients for UF estimation

Table A1. Exponential fit coefficients for UF estimation

	USA		**South Korea**	**EU**	**Japan**
Coefficient	**Fleet**	**Individual**	**Fleet**	**Fractional**	**Fractional**
$C1$	10.52	13.1	26.5	26.25	11.9
$C2$	-7.282	-18.7	77.9	-38.94	-32.5
$C3$	-26.37	5.22	-1100	-631.05	89.5
$C4$	79.08	8.15	2960	5964.83	-134
$C5$	-77.36	3.53	-1960	-25094.6	98.9
$C6$	26.07	-1.34		60380.21	-29.1
$C7$		-4.01		-87517.2	11.9
$C8$		-3.9		75513.77	-32.5
$C9$		-1.15		-35748.8	89.5
$C10$		3.88		7154.94	-134
Reference	[33]	[33]	[75]	[206]	[206]
Normalized distance	400 miles		600 km	800 km	400 km
Test cycles and procedures	SAE J2841 and SAE J1711		SAE J2841 and SAE J1711[33, 34]	WLTP[44, 68, 69, 206]	

Regulatory test cycles in the U.S, EU, Japan, and China

Table A2. Comparison of test cycle parameters used for range, fuel economy, energy and emission estimation in different regions

Driving Cycle Parameters	***Units***	**NEDC**	**WLTP**	**FTP75**	**HWFET**	**CAFE**	**JC08**	**CLTC**
Country		**EU [72, 207]**		**US [91, 207, 208]**			**Japan [74]**	**China [209, 210]**
Cycle distance	*km*	11	23.25	11.99	16.5		8.17	14.5
Average speed	*kmph*	33.6	46.5	31.5	77.7	43	24.4	29
Maximum speed	*kmph*	120	131	91.2	96.4		81.6	114
Cycle time	*s*	1180	1800	1369	765		1204	1800
Average Acceleration	ms^{-2}	0.53	0.53	0.5	0.19	0.42	0.42	0.45
Average Deceleration	ms^{-2}	-0.75	-0.58	-0.58	-0.22	-0.49	-0.45	-0.5
Acceleration fraction	*%*	20.9	30.9	39.7	44.2	40.8	35.9	28.7
Deceleration fraction	*%*	15.1	28.6	34.7	38.8	35.7	33.6	26.4
Cruising fraction	*%*	40.3	27.8	8	16.5	10.1	1.7	22.8
Idling fraction	*%*	23.7	13.4	17.6	0.5	13.2	28.7	22.1
Driving Style(s)		Urban, Extra Urban	4-phase$^{\$}$	Urban	Highway			

$^{\$}$Divided into 4 phases(low, medium, high, and extra high) with the average speeds increasing with each subsequent phase representative of urban (up to 35 mph) , suburban (up to 47 mph), up to 60 mph, and up to 81 mph driving, respectively.

NEDC – New European Driving Cycle

WLTP – Worldwide Harmonized Light duty vehicle Test Procedure

FTP75 –Federal Test Procedure. Urban Dynamometer Driving Schedule (UDDS) plus the first 505 seconds of another UDDS

HWFET – Highway Fuel Economy Test cycle

CAFE – Corporate Average Fuel Economy

JC08 Japanese Test Cycle up to 2020 and from 2030 onwards will be replaced by WLTP

CLTC – China Light-duty Vehicle Test Cycle. CLTC is currently under development and is expected to replace the WLTP. China currently uses modified NEDC and will use the WLTP until the transition to CLTC is complete

Summary of UF estimates from various studies

Table A3. Summary of UF estimates from various studies

PHEV Model	Range (miles)#	N Vehicles	Reported UF	Label UF$	% Deviation from Label UF	Region	Data Source
Chevy Gen1 Volt	35/38	1867	0.745	0.573/0.591	**28.0%**	U.S.[53]	In use data logging
Chevy Gen1 Volt	35	787	0.724	0.573	**26.4%**	U.S.[86]	
Chevy Gen1 Volt	38	618	0.739	0.600	**23.2%**		
Chevy Gen1 Volt	35/38	48000-63000	0.74	0.573/0.591	**27.1%**	U.S. and Canada[56]	
Chevy Gen2 Volt	50	48000-63000	0.8	0.707	**13.2%**		
Ford Cmax	20	5368	0.328	0.396	-17.2%	U.S.[86]	
Ford Cmax	20	10253	0.328	0.396	-17.2%	U.S.[100]	
Ford Fusion	20	5803	0.352	0.396	**-11.1%**	U.S.[86]	
Ford Fusion	20	12842	0.343	0.396	**-13.4%**	U.S.[100]	
Toyota Prius	11	1523	0.164	0.247	-33.6%	U.S. [86, 100]	
Honda Accord	13	189	0.222	0.284	-21.8%		
BMW i3 REX	72/80	8309	0.921	0.793/0.821	**13.7%**	U.S.[100]	
Chevy Gen1 Volt	38	1831	0.785	0.591	**32.8%**	U.S. and Canada[60]	User reported and aggregate OBD telematics data
Toyota Prius	11	88	0.304	0.247	**23.1%**	Germany[60]	
Opel Ampera	38	25	0.723	0.591	**22.3%**		
Mitsubishi Outlander	23	46	0.469	0.442	**6.1%**		
Volvo V60	24	15	0.486	0.534	-9.0%		
Audi A3	31	197	0.59	0.755	-21.9%	Norway [211]	Survey of existing PHEV users
Opel Ampera	52	46	0.72	0.874	-11.9%		
BMW C350e	19	11	0.41	0.607	-32.5%		
VW Golf GTE	31	283	0.57	0.755	-12.6%		
Mitsubishi Outlander	32	806	0.55	0.766	-11.2%		
Toyota Prius	16	67	0.38	0.536	-6.7%		
Volvo V60	31	104	0.51	0.755	-11.3%		
Opel Ampera	51	1190	0.44-0.48	0.77	-40.3%	Netherlands[212]	In use data logging
Chevrolet Volt	51	203	0.44-0.49	0.77	-40.3%		
Toyota Prius	15	906	0.15-0.19	0.5	-66.0%		
Volvo V60	31	2738	0.23-0.3	0.67	-61.2%		
Mitsubishi Outlander	32	5390	0.29-0.35	0.68	-52.9%		
Ford Cmax	20	229	0.28-0.37	0.64	-48.4%		
Audi e-tron	31	1345	0.21-0.34	0.67	-58.2%		
VW Golf GTE	31	2235	0.21-0.3	0.66	-63.6%		
VW Passat GTE	31	698	0.3	0.67	-55.2%		
MercedesC 350e	19	895	0.25-0.4	0.55	-40.0%		
BMW i3	72/80	86	0.84-0.89	0.86	0.0%		

#Range refers to charge depleting range estimated under region specific test cycles and procedures

$ Germany, Norway, and Netherlands Range and Label UF based on NEDC. U.S. and Canada Range and UF based on U.S. EPA combined city/highway UF.

Tests for statistical significance

Table A4. t-test results- Comparing UF of every vehicle observed with J2841 IUF

UF_{obs} and IUF_{ref}	**t Test Test Statistic**	**Prob > |t|**	**Prob < t**	**Prob > t**
Prius	-4.547	0.0002	<.0001	1.000
Energi	-2.237	0.030	0.015	0.985
Gen1Volt	0.695	0.491	0.755	0.245
Gen2Volt	-2.538	0.016	0.008	0.992
p-values significant at 5% are shown in italics				

Table A5. t-test results- Comparing UF of every vehicle observed with J2841 FUF

UF_{obs} and FUF_{ref}	**t Test Test Statistic**	**Prob > |t|**	**Prob < t**	**Prob > t**
Prius	-2.769	0.012	0.006	0.994
Energi	-0.394	0.696	0.348	0.652
Gen1Volt	2.944	0.0053	0.997	0.0026
Gen2Volt	-0.897	0.376	0.188	0.812
p-values significant at 5% are shown in italics				

Table A6. Equivalence tests- Comparing UF of every vehicle observed with J2841 IUF

	Equivalence Region	$H_0: UF_{obs} \leq IUF_{ref} - \Delta$		$H_0: UF_{obs} \geq IUF_{ref} + \Delta$	
		t-Ratio	p-Value	t-Ratio	p-Value
Prius	[0.269,0.317]	-3.620	0.999	-5.475	<.0001
Energi	[0.410,0.502]	-0.800	0.786	-3.673	*0.000*
Gen1Volt	[0.614,0.688]	2.02	*0.024*	0.605	0.274
Gen2Volt	[0.721,0.797]	-1.339	0.905	-3.738	*0.0003*
α=0.05, $\Delta = 0.2\ (\text{Cohen's d}) \times \text{sample Std. Dev.}$					

Table A7. Equivalence tests- Comparing UF of vehicle observed with J2841 FUF

	Equivalence Region	$H_0: UF_{obs} \leq FUF_{ref} - \Delta$		$H_0: UF_{obs} \geq FUF_{ref} + \Delta$	
		t-Ratio	p-Value	t-Ratio	p-Value
Prius	[0.223,0.271]	-1.842	0.960	-3.697	0.001
Energi	[0.351,0.443]	1.043	0.151	-1.830	0.037
Gen1Volt	[0.551,0.625]	4.257	<0.0001	1.631	0.945
Gen2Volt	[0.669,0.745]	0.303	0.382	-2.096	0.022
α=0.05, $\Delta = 0.2\ (\text{Cohen's d}) \times \text{sample Std. Dev.}$					

Table A8. Post-hoc two-tailed t tests achieved power and effect size for given α and sample size

	Observed IUF and J2841 IUF		Observed IUF and J2841 FUF	
	Power (1-β)	Effect Size d	Power (1-β err prob)	Effect Size d
Prius	0.992	0.975	0.947	0.801
Energi	0.597	0.312	0.512	0.281
Gen1Volt	0.109	0.1111	0.463	0.291
Gen2Volt	0.690	0.421	0.44	0.189
α=0.05, Effect size d=0.2 (small), d=0.5(medium), d=0.8 Large				

Daily VMT descriptive summaries comparisons between NHTS and Observed PHEVs

Table A9. NHTS and observed PHEVs: DVMT descriptive statistics

	Quantiles					
	10	**25**	**50**	**75**	**90**	**Mean**
NHTS	5	12	26	50	85.5	40
Prius	8.7	19.2	35.2	56.9	94.7	46
Energi	8.3	16.9	34.7	61.7	95.4	46
Gen1Volt	7.1	16.2	33.8	60.6	88.6	44
Gen2Volt	7.8	16.0	29.3	47.8	75.4	39
	Median Absolute Deviation	**Skewness**	**Kurtosis**	**Lower 95% Mean**	**Upper 95% Mean**	**IQR**
NHTS	16	5.2	52.0	39.5	40.7	38.0
Prius	18	3.9	28.1	44.7	46.8	37.7
Energi	20	3.8	26.3	45.5	47.0	44.8
Gen1Volt	20	2.8	14.5	43.7	45.1	44.4
Gen2Volt	15	5.1	48.5	38.2	39.7	31.8

Table A10. KS test report: Comparing CDF of DVMT between NHTS and observed PHEVs

	KS	D =Max|F1-F2|	NHTS CDF at D	Observed DVMT at D	Prob >D
Prius	0.058	0.152	0.416	20	<.0001*
Energi	0.0638	0.137	0.567	30	<.0001*
Gen1Volt	0.056	0.125	0.508	26	<.0001*
Gen2Volt	0.043	0.099	0.303	14	<.0001*
	KSa	**D+ =Max(F1-F2)**	**Prob > D+**	**D-=Max(F2-F1)**	**Prob > D-**
Prius	11.42	0.0069	0.578	0.1519	<.0001*
Energi	13.72	0.0057	0.520	0.1376	<.0001*
Gen1Volt	11.85	0.0086	0.2678	0.1250	<.0001*
Gen2Volt	8.92	0.0427	<.0001*	0.0999	<.0001*

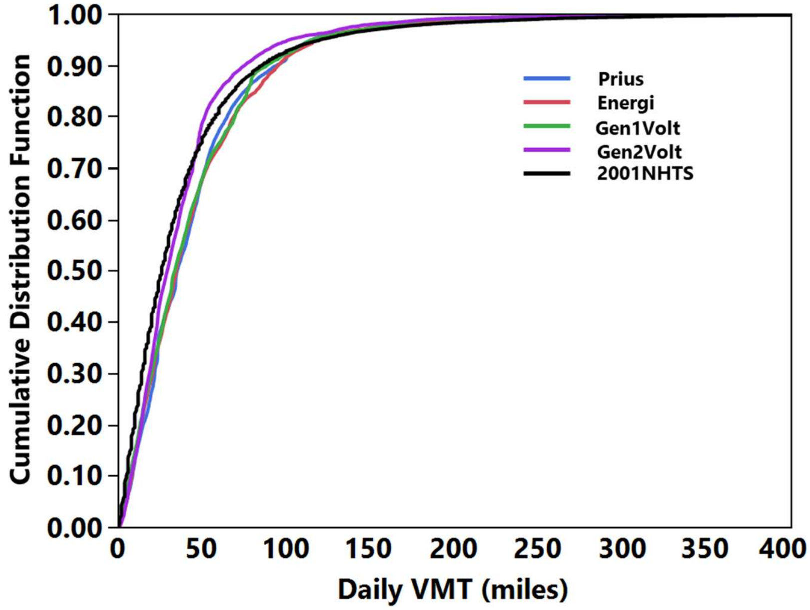


Figure A1. Expanded CDF plot of observed PHEVs and NHTS

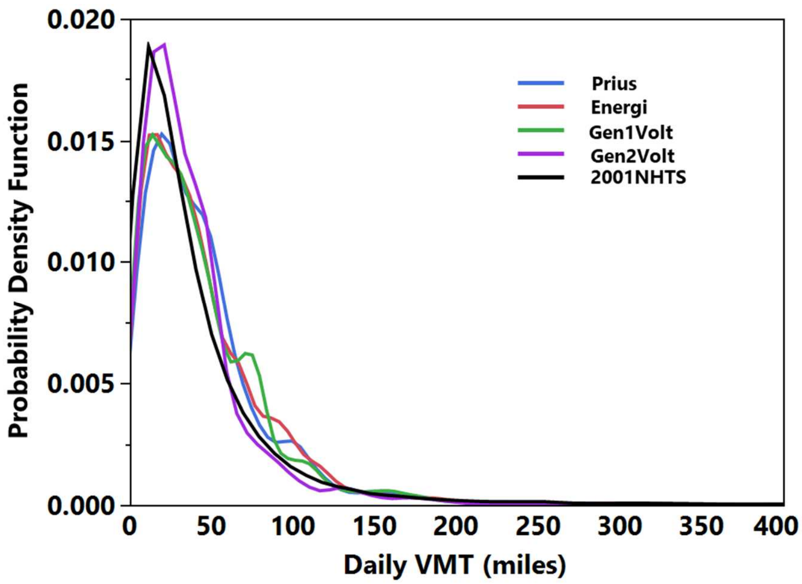


Figure A2. Expanded PDF plot of observed PHEVs and NHTS

Sampling comparisons

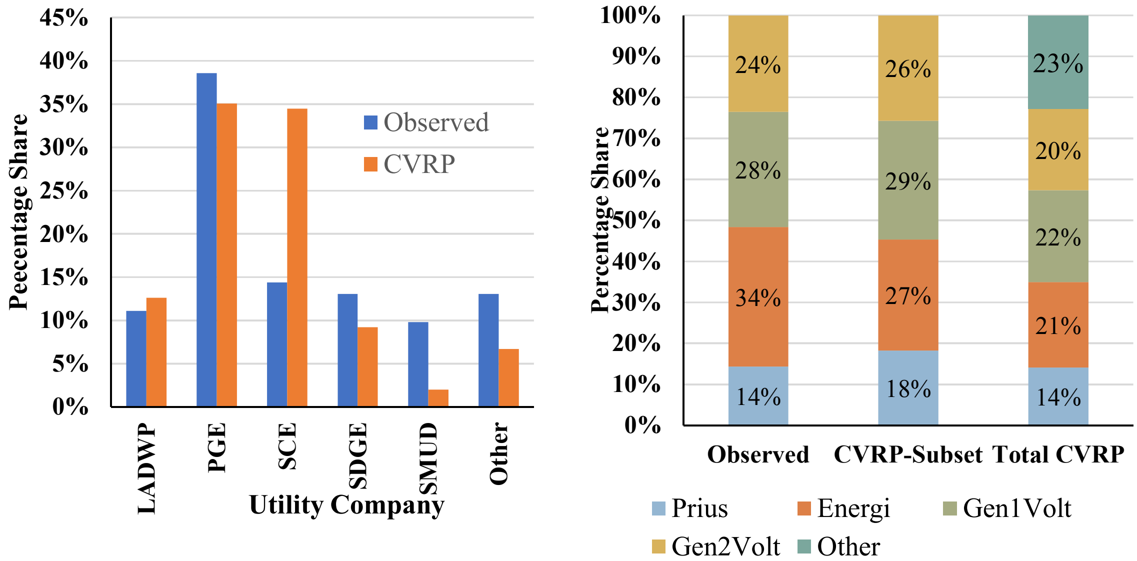
Table A11 Comparison between observed PHEVs and Clean Vehicle Rebate Project(CVRP) database by utility company and PHEV model

Observed PHEVs (This Study)					
Utility	**Observed PHEVs**	**Prius**	**Energi**	**Gen1Volt**	**Gen2Volt**
LADWP	17	2	5	4	6
PGE	59	11	16	17	15
SCE	22	2	7	6	7
SDGE	20	3	9	5	3
SMUD	15	1	7	6	1
Other	20	3	8	5	4
Total	***153***	***22***	***52***	***43***	***36***

Number of rebates issued under the California Clean Vehicle Rebate Project (CVRP)2012-2018 [82]						
Utility[3]	**CVRP Subset**[$]	**Total CVRP**	**Prius**	**Energi**	**Gen1Volt**	**Gen2Volt**
LADWP	11278	13688	1569	2212	4021	3476
PGE	5848	7607	1028	1417	1695	1708
SCE	30922	39550	5499	8306	8746	8371
SDGE	29911	39711	6429	8242	8496	6744
SMUD	7803	10409	1217	2861	1999	1726
Other	1661	2343	251	580	404	426
Total	***87423***	***113308***	***15993***	***23618***	***25361***	***22451***

[$]Subset of CVRP includes the rebates issued to the PHEV models analyzed in this study: Toyota Plug-in Prius , Ford CMax and Fusion Energi , Gen1 Chevrolet Volt (MY 2011-2015) and Gen2 Chevrolet Volt (MY 2016 onwards). Total CVRP rebates includes rebates issued to all PHEV models between 2012-2018

[3] Investor owned utilities (IOUs) are Pacific Gas & Electric (PGE) , San Diego Gas & Electric(SDGE), and Southern California Edison (SCE). Sacramento Municipal Utility District (SMUD) and Los Angeles Department of Water and Power (LADWP) are the two public owned utilities (POUs)



(left) (right)

Figure A3 (Left) Percentage of PHEVs by utility company: observed and CVRP database ; (Right) Percentage of PHEVs by PHEV model : observed and CVRP database

Table A12 Sociodemographic attributes comparisons between the 2017 NHTS California Add-on[84] and this study

Household Ownership	**Own**	**Rent**	**Gender**	**Male**	**Female**
NHTS-CA	18436(71%)	7444(29%)	NHTS-CA	26554(48%)	29180(52%)
This Study	122(80%)	30(20%)	This Study	106(69%)	44(29%)
Educational Attainment	**Less than a high school graduate**	**High school graduate or GED**	**Some college or associates degree**	**Bachelor's degree**	**Graduate or professional degree**
NHTS-CA	10204(18%)	7391(13%)	15043(27%)	11837(21%)	11282(20%)
This Study			18(12%)	49(32%)	86(56%)
Income	**Less than \$50,000**	**\$50,000 to \$99,999**	**\$100,000 to \$149,999**	**\$150,000 to \$199,999**	**\$200,000 and more**
NHTS-CA	9260(37%)	7541(30%)	4495(18%)	1844(7%)	2169(9%)
This Study	11(7%)	33(22%)	33(22%)	31(20%)	43(28%)
Household Size	**1**	**2**	**3**	**4**	**5+**
NHTS-CA	8459(32%)	10928(42%)	3218(12%)	2320(9%)	1187(5%)
This Study	19(12%)	63(41%)	29(19%)	29(19%)	12(8%)
Number of Drivers	**0**	**1**	**2**	**3**	**4+**
NHTS-CA	935(4%)	9755(37%)	12971(50%)	1855(7%)	596(2%)
This Study		23(15%)	109(71%)	14(9%)	6(4%)

Average annual VMT and long-distance travel

Table A13 Average annual VMT reported in literature

	This study	EV project[86]	CARB[100]	Voltstats[102]	MyFord Mobile[137]
Prius	16432	15136	15283	12694	
Energi	16705	12403	13920/15076		12674/14058
Gen1 Volt	16038	12238	12403	8517-10828	
Gen2 Volt	14115				

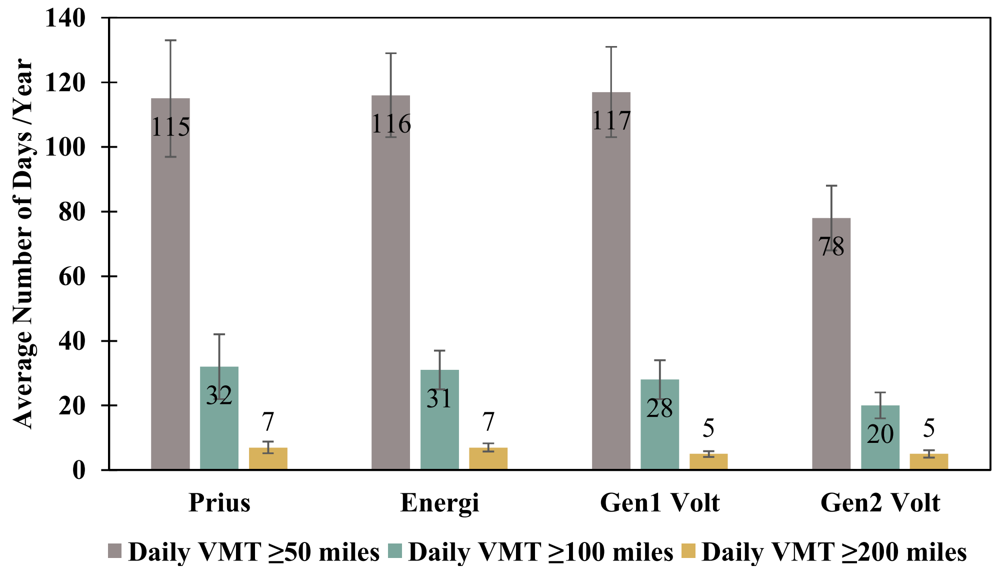


Figure A4 Average number of days/year daily VMT exceeded 50, 100, 200 miles or more.

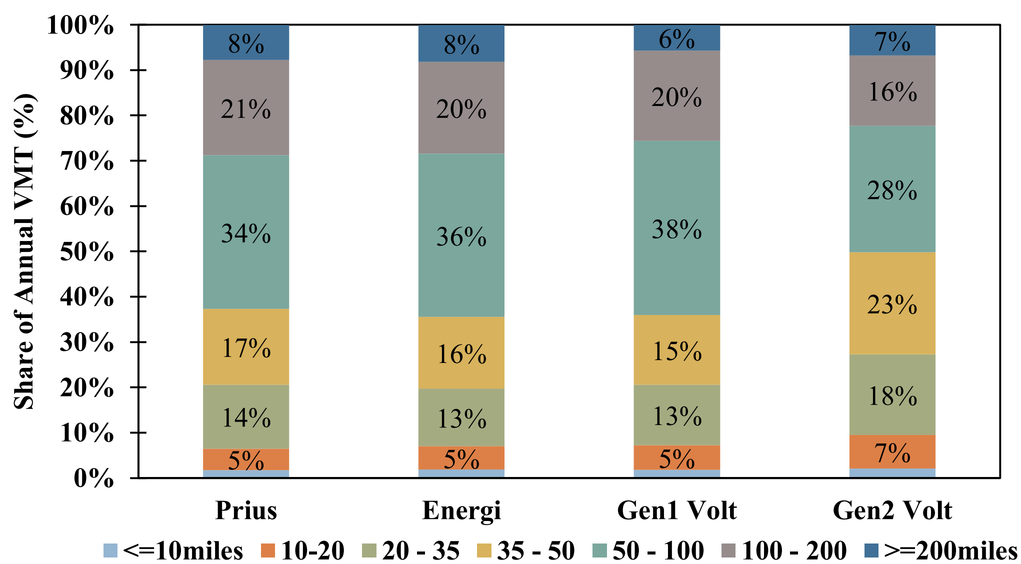
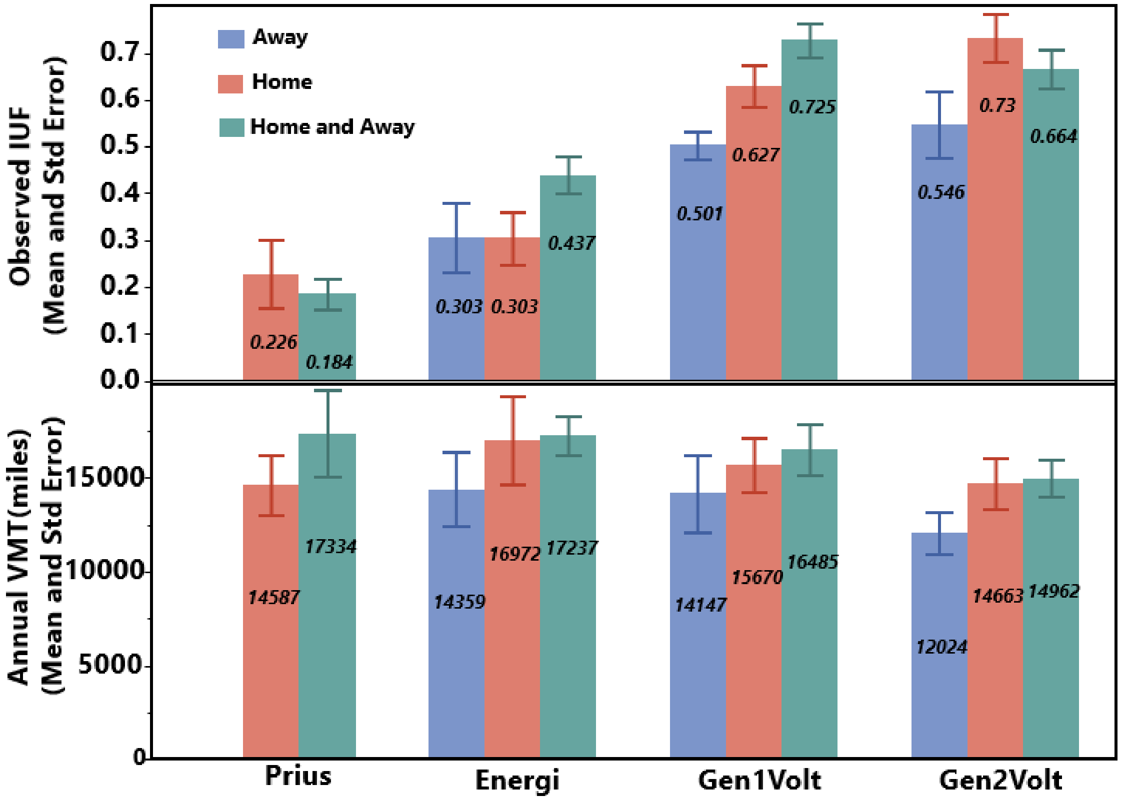


Figure A5 Share of annual VMT binned by daily VMT distance

Charging accessibility, annual VMT, and observed IUF



	N Vehicles	Away N(%)	Home N(%)	Home and Away N(%)
Prius	22	-	9 (41%)	13 (59%)
Energi	52	8 (15%)	16 (31%)	28 (54%)
Gen1 Volt	43	2 (5%)	19 (44%)	22 (51%)
Gen2 Volt	36	10 (28%)	12 (33%)	14 (39%)
Total	*153*	*20 (13%)*	*56 (37%)*	*77 (50%)*

Figure A6 Relationship between charging accessibility, annual VMT, and observed IUF. Share of PHEVs by type and charging access shown inset.

Appendix B
Supporting information for Chapter 3

This section summarizes the results of the power analysis regression models, and the rationale behind excluding interaction terms in the OLS regression models as well as their relative contribution to the overall model effects.

Table B1 A-priori Test: Compute sample size for a given α, power, and effect size

	Effect Size	**α Err prob**	**Power (1-β)**	**Non-centrality parameter**	**Critical F**	**Sample Size**	**Actual Power**
Short-range PHEVs	0.35	0.05	0.95	25.9	2.08	**74**	0.95
Long-range PHEVs	0.72	0.05	0.95	29.04	2.25	**40**	0.95

Table B2 Post-hoc Test: Compute achieved power for a given α, sample size, and effect size

	Effect Size	**α Err prob**	**Non-centrality parameter**	**Critical F**	**Actual Power**
Short-range PHEVs	1.02	0.05	75.48	2.08	**0.999**
Long-range PHEVs	1.84	0.05	145.71	2.07	**0.999**

Table B1 presents the results of the A-priori test that determines the number of samples (number of PHEVs) required to given the significance level (α=5%), power (1-β), number of predictors (eight, the 4 driving and 4 charging related PCs) , and effect size. The probability of Type I and Type II error is α and β respectively. Table B2 is a post-hoc test which calculates the power achieved given the significance level, sample size and effect size. From Table B2, we can see that the achieved power of the OLS regression models is beyond sufficient.

Table B3 presents the regression model estimates and the model fit summaries with interaction effects. When I compare the main effects only model results (**Error! Reference source ot found.**Table 3.9-Table 3.10) and the model results with main and interaction effects in Table B3, the estimates changed slightly. However, their statistical significance almost remained identical to the main effects only model, even after the inclusion of interaction effects across all the four models in Table . The only change was observed when interacting *PC2.Chg * PC2.Drv (Home-less frequent and deep cycle * Long-distance travel*) of short-range PHEVs, where the predictor PC2.Chg is statistically significant, whereas in the main effects only model in **Error! Reference source not found.**Table 3.9, t was not statistically significant at 5%. Since the interaction terms were not statistically significant, no additional analyses was performed to assess their relative importance and only the main effects model were considered in my analysis.

Table B3 OLS Regression Model Results with Interaction Effects

	DV = ΔUF = Observed UF—Label UF	SR PHEVs N = 74		SR PHEVs N = 74		SR PHEVs N = 74		LR PHEVs N = 79	
PCs		**Estimate**	**Prob > |t|**	**Estimate**	**Prob > |t|**	**Estimate**	**Prob > |t|**	**Estimate**	**Prob > |t|**
	Intercept	−0.067	0.006	−0.055	0.023	−0.069	0.009	−0.044	0.010
PC1.Chg	Away-frequent and deep cycle	**0.09**	**0.012 ***	**0.101**	**0.005 ***	**0.089**	**0.015 ***	**0.046**	**0.001 ***
PC2.Chg	Home-less frequent and deep cycle	0.046	0.088	**0.057**	**0.036 ***	0.045	0.118	**0.042**	**0.003 ***
PC3.Chg	Home-frequent and shallow cycle	**0.054**	**<0.0001 ***	**0.053**	**<0.0001 ***	**0.053**	**<0.0001 ***	**0.100**	**<0.0001 ***
PC4.Chg	Home and away-balanced utilization	**0.058**	**0.001 ***	**0.056**	**0.001 ***	**0.059**	**0.000 ***	**0.049**	**0.018 ***
PC1.Drv	High usage intensity	**−0.07**	**<0.0001 ***	**−0.077**	**<0.0001 ***	**−0.070**	**<0.0001 ***	**−0.099**	**<0.0001 ***
PC2.Drv	Long-distance travel	−0.016	0.297	−0.018	0.234	−0.015	0.306	**−0.121**	**<0.0001 ***
PC3.Drv	Conservative driving	−0.022	0.324	−0.022	0.302	−0.021	0.346	0.011	0.340
PC4.Drv	High energy intensity	**−0.071**	**<0.0001 ***	**−0.072**	**<0.0001 ***	**−0.072**	**<0.0001 ***	**−0.066**	**<0.0001 ***
PC2.Chg * PC3.Drv	Home-less frequent and deep cycle * Conservative driving	−0.023	0.679	-		-		-	
PC2.Chg* PC2.Drv	Home-less frequent and deep cycle * Long-distance travel	-		−0.008	0.802	-			
PC4.Chg * PC1.Drv	Home and away-balanced utilization * High usage intensity	-		-		−0.021	0.071	-	
PC3.Chg * PC2.Drv	Home-frequent and shallow cycle * Long-distance travel	-		-		-		0.028	0.096
		SRPHEV Model Fit		**SRPHEV Model Fit**		**SRPHEV Model Fit**		**LRPHEV Model Fit**	
	***R*²**	0.773		0.772		0.783		0.687	
	Adj. *R*²	0.741		0.740		0.753		0.646	
	AIC	−109.83		−109.70		−113.42		−102.98	
	BIC	−88.74		−88.61		−92.33		−80.862	

* Factors that are statistically significant at 5%; AIC and BIC-Akaike and Bayesian Information Criterion

Appendix C
Supporting information for Chapter 4

Survey design and sampling comparisons

I provide an overview of the online survey and compare select indicators of the 73 California households studied in Chapter 4 with state-wide surveys.

Online survey

Online survey was administered between June 2015 and July 2017 to current PEV owners who purchased or leased their PEV in the last 4 years. Participants were randomly sampled from the Clean Vehicle Rebate Project (CVRP) database and vehicle registration records. Stratified random proportionate sampling strategy was primarily used to recruit participants. The stratification was based on the territorial coverage of the three major investor owner (IOUs) and the two major publicly owned utilities (POUs). The unit of observation is at the household level for household level analysis and the study population is the list of households who purchased or leased their PEV (PHEVs and BEVs) in the last 4 years. The sampling frame is the list of PEV owners and lessors in CVRP database and the registration records in the state of California.

Table C-1. Socioeconomics, demographics, and vehicle characteristics sampling comparisons between this study and 2017 National Household Travel Survey[84, 178] (NHTS) California (CA) add-on participants

	NHTS-CA	This Study
Home ownership		
Own	18436(71%)	66(90%)
Rent	7444(29%)	7(10%)
Gender		
Male	26554(48%)	51(70%)
Female	29180(52%)	22(30%)
Educational Attainment		
Less than a high school graduate	10204(18%)	1(1%)
High school graduate or General Educational Development	7391(13%)	8(11%)
Some college or associate degree	15043(27%)	18(25%)
Bachelor's degree	11837(21%)	3(4%)
Graduate or professional degree	11282(20%)	43(59%)
Income		
Less than $50,000	9260(37%)	3(4%)
$50,000 to $99,999	7541(30%)	14(19%)
$100,000 to $149,999	4495(18%)	10(14%)
$150,000 to $199,999	1844(7%)	15(21%)
$200,000 and more	2169(9%)	31(41%)
Household size		
1	8459(32%)	
2	10928(42%)	30(41%)
3	3218(12%)	17(23%)
4 or more	3507(14%)	26(36%)
Number of drivers		
0	935(4%)	
1	9755(37%)	1(1%)
2	12971(50%)	67(92%)
3 or more	2451(9%)	5(7%)
Household vehicle count		
0	966(7%)	
1	4084(31%)	
2	4490(35%)	73(100%)
3 or more	3505(27%)	
Share by vehicle class		
Car	56%	34%
Light truck	44%	66%
Average annual VMT		
ICE	9501	8645
BEV	10503	12737

Table C-2. Sampling comparisons between observed and California Clean Vehicle Rebate Project[82] (CVRP) rebates issued to BEVs between 01/2015 and 01/2020**.**

Utility	**Observed BEVs**	**Nissan Leaf**	**Chevrolet Bolt**	**Tesla**[&]
Los Angeles Department of Water and Power (LADWP)	10	1	6	3
Pacific Gas and Electric (PGE)	21	14	4	3
Southern California Edison (SCE)	16	6	5	5
San Diego Gas and Electric (SDGE)	13	5	2	6
Sacramento Municipal Utility District (SMUD)	6	2	2	2
Other	7	2	2	3
Total	73	30	21	22
Percentage share (%)		***41%***	***29%***	***30%***

Utility	**CVRP Subset^**	**Total CVRP**	**Nissan Leaf**	**Chevrolet Bolt**	**Tesla**[&]
LADWP	10930	17516	707	2039	8184
PGE	57256	76099	11630	10348	35278
SCE	41217	57272	3113	5692	32412
SDGE	14409	19543	1700	2039	10670
SMUD	3359	4218	645	579	2135
Other	9288	12657	1315	1690	6283
Number of BEV rebates issued	*136459*	*187305*	*19110*	*22387*	*94962*
Percentage share of CVRP subset			***14%***	***16%***	***70%***
Percentage share of Total CVRP		***73%***	***10%***	***12%***	***51%***

^Subset of CVRP denotes the subset of all BEV rebates issued to the three BEV models analyzed in this study (Nissan Leaf, Chevrolet Bolt and Tesla). &CVRP does not categorize Tesla vehicles into Model S , Model X or Model 3.

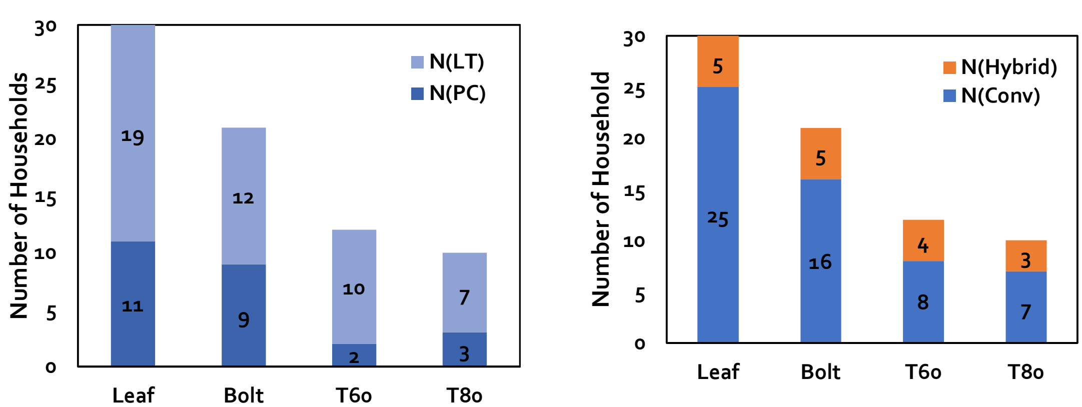
Table C-1 compares the key respondent indicators with state-wide sample statistics collected during the 2017 National Household Travel Survey, California add-on. Nearly 12,396 of the respondents indicated that they are willing to participate in the data logger study. The overall response rate for the survey was 18% and 82% (14,000) of these respondents completed the survey. The survey data has more depth of information and 15% more completed responses than similar studies carried at national level[161, 187] and 50% more completed responses than international studies[213]. The unit of observation is at the household level for household level analysis and the study population is the list of households who purchased or leased their PEV in the last 4 years. The sampling frame is the list of PEV owners and lessors in CVRP database and the registration records in the state of California. Stratified random proportionate sampling strategy was primarily used to recruit participants. Due to logistical concerns, travel and overheads associated with logger installation and uninstallation process, convenience sampling strategy was used as a secondary option when needed. The stratification was based on the territorial coverage of the three major investor owned utilities (Pacific Gas and Electric-PGE , Southern California Edison-SCE, San Diego Gas and Electric-SDGE) and the two major publicly owned utilities (Los Angeles Department of Water and Power-LADWP and Sacramento Municipal Utility Devices-SMUD). Overall, the observed BEVs represent nearly 75% of the models that were issued the CVRP rebate during 2015-2020, Table C-2.

Representativeness and generalizabilitySummary of key variables relevant to this work , sampling comparisons of the 73 households observed with the 2017 National Household Travel Survey (California add-on), and the CVRP database are outlined in the Supporting Information Tables S1-S3. I used the 2017 NHTS-California add-on because it is more recent , geographically, and temporally within with the data collection period of this study. There is a possibility of self-selection , but it is reflective of current market trends, early adopter buying preferences, and presents a reasonable snapshot of current BEV buyers. Correlation among socio-economics and demographic indicators and self-selection bias of PEV owners is inherent and it is prohibitively expensive (data collection period, logger installation and uninstallation logistics, participant availability, and staff hours) to eliminate all confounding and conflating variables by controlling for every such correlation[17]. The over (or) under-representation of the logger study participants by household size and number of drivers is just a natural consequence of selecting only 2-car households.

Observed ICE and BEV Attributes

ICE Class and Fuel Economy

Out of the 73 ICEs, 48 belonged to the Light Truck (LT) class and alternative fuel or hybrid vehicles accounted for 17 of the 73 ICEs, Figure C-1



(a) (b)

Figure C-1. Number of households by BEV type, ICE vehicle class and ICE fuel type

(a) Number of households by BEV type ICE vehicle class: Passenger Car(PC) or Light Truck(LT) . Light Truck class includes station wagons, sports utility vehicles (SUV), vans, and pickup trucks.

(b) Number of households by BEV type and ICE fuel type: Conventional gasoline or hybrid. Of the 17 Hybrid vehicles, 4 were flex-fuel (two in T60 households, one each in T80 and Bolt household).

Figure C-2 shows the distribution of observed ICE fuel economy in MPG with their respective EPA window sticker label values.

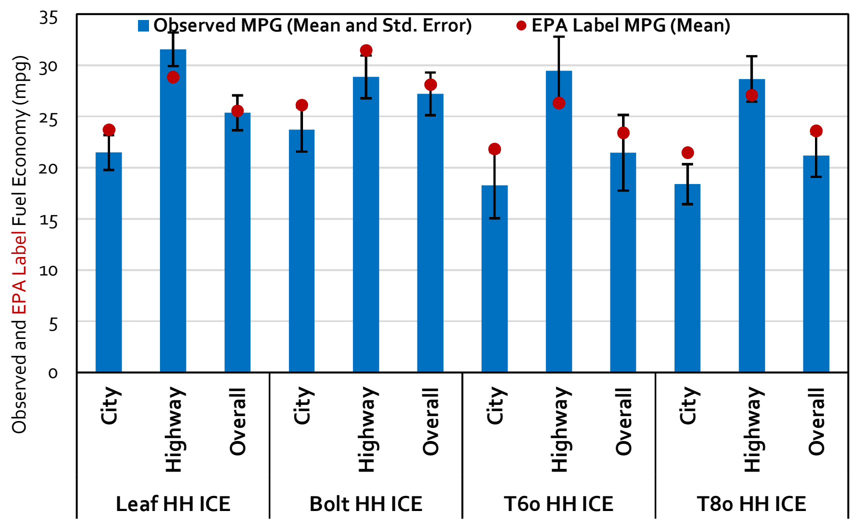


Figure C-2. Observed and EPA label fuel economy[88] (mpg) of the ICE by driving styles in different BEV households(HHs). Blue columns and the black bars depict the mean and standard error of observed fuel economy. Dark red dots are the EPA label average fuel economy.

<u>Charging accessibility and incentives availed</u>

Table C-3. Overview of data logger study participants' charging access and incentives availed

	Leaf HH	Bolt HH	T60 HH	T80 HH	Total
Charger location (Home and/or Away)					
Away	2	3	0	0	*5(7%)*
Home	9	10	3	2	*24(33%)*
Home and Away	19	8	9	8	*44(60%)*
Availability of charger at workplace					
No	13	8	4	5	*19(26%)*
Yes	8	8	5	3	*30(41%)*
Missing response/I don't know	*8*	*5*	*3*	*2*	*24(33%)*
Household on preferential time of use BEV rates					
No (currently and no plans in future)	9	11	1	2	*23(31%)*
No(currently but plan to in future)	4	2	2	2	*10(14%)*
Yes(currently)	17	8	8	5	*38(52%)*

Missing response/I don't know	-	-	1	1	*2(3%)*
Availed California Clean Air Vehicle Decal (Carpool stickers*)					
No	11	3	1	1	*16(22%)*
Yes	19	8	11	9	*57(78%)*
Availed California Clean Vehicle Rebate Project Purchase Subsidy					
Yes	29	21	12	10	*72(99%)*
Missing response/I don't know	1	-	-	-	

**California Department of Motor Vehicles issue decals to qualified vehicles meeting emission standards that allows single occupancy use of HOV or carpool lanes. CAV decals potentially reduce commute time by 28% and save roughly $540 per vehicle in avoided tolls[214]*

BEV Usable Capacity, Range and Driving Efficiency

Usable battery capacities are proprietary and confidential information and the usable range is a function of energy intensity of driving (kWh/mile). I calculated the usable battery capacity from the charging session data using an ordinary least squares regression model fitted between the charged SOC (independent variable) and the charging electrical energy in kWh (dependent variable) for every BEV. The electrical energy charged corresponding to 100% SOC was estimated to be the usable battery capacity. I then calculated the electrical energy efficiency of driving as the ratio of aggregate net energy required for driving to its aggregate VMT for every BEV, where the net driving energy is the sum of energy discharged and the energy from regenerative braking. In this dataset, the usable range, i.e. maximum possible range corresponding to a fully charged BEV on average was 5-16% lower than the respective label values. **Figure C-3** of depicts the distribution (mean and standard error bar) of the usable range of observed BEVs alongside the EPA window sticker label range. The accompanying Table S3 summarizes the efficiency (kWh/mile) under different driving styles , and the usable battery capacity. Figure S3 and Table S3 show the relevant attributes of the upgraded BEV that were considered for scenarios *S4-S6.*

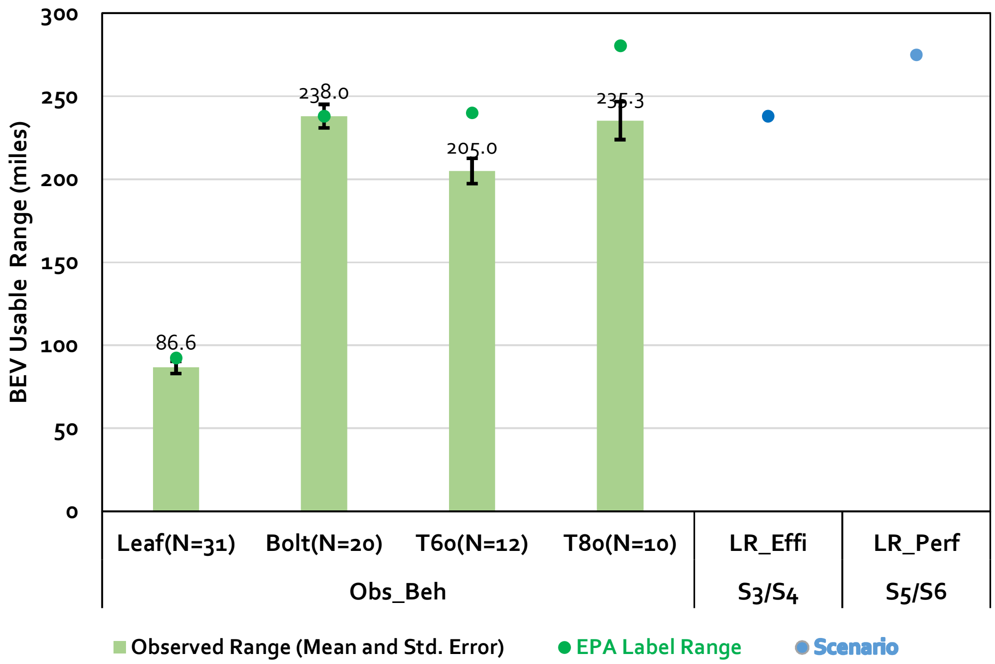


Figure C-3. Observed and EPA label range[88] (miles) of the BEV by driving styles. Light green columns and the black bars depict the mean and standard error of observed range. Dark green dots are the EPA label average fuel economy. Blue dots show the upgraded range for *S3 LREffi and S4 LREffi FullChg and S5 LRPerf and S6 LRPerf FullChg* scenarios.

Table C-4. Average driving efficiency (kWh/mile) by driving style, observed battery capacities (kWh) and range (miles) and EPA label range (miles).

	Efficiency				**Label**	**Observed***	
	City	***Mixed***	***Highway***	***Overall***	***Range***	***Battery Capacity***	***Range***
Leaf (N=30)	0.238	0.198	0.276	0.248	93	22	87
Bolt (N=21)	0.240	0.218	0.273	0.247	238	58	238
T60(N=12)	0.442	0.254	0.307	0.350	240	72	205
T80(N=10)	0.452	0.263	0.317	0.353	280	83	235
Longer-range efficiency oriented BEV&	0.240	0.218	0.273	0.247		58.1	238
Longer-range sportier performance oriented BEV$	0.464	0.298	0.349	0.384		105	273
400-mile BEV**	0.320	0.332	0.347	0.332	402		402

*Observed range and battery capacities refer to their usable values.

& For scenarios *S3 Select and S4 Select FullChg*. Average usable range, efficiency, and battery capacity of the 21 Bolts used. The *S3 Select and S4 Select FullChg* scenarios thereby defaults to *S1 Select and S2 Select FullChg so excluded from the charts and tables as needed.*

$ For scenarios *S5 Select and S6 Select FullChg*. Average usable range, efficiency, and battery capacity of 20 T80s monitored throughout the entire study period (2015-ongoing). It includes 10 additional T80s that were dropped because they were out of scope of this study which focuses only on 2-car households.

** 2020 Tesla Model S Long Range Plus was chosen as the representative BEV. EPA label values of driving efficiency from the fuel economy[88, 215] database (vehicle id 42755) was used. To account for divergence from real-world energy consumption, I assumed real-world driving energy to be 15% more than label estimates. This scaling by 15% was approximated using the average driving efficiency of all 21 Teslas observed in this study (twelve T60 and ten T80s).

Both the Chevrolet Bolt and entry level Tesla Model S with 70kWh rated battery capacity have comparable range of 235 miles but there are few significant differences. Tesla Model S is rear-wheel drive large car equipped with a 285 kW drivetrain motor and consumes 0.38 kWh/mile under city driving. The Bolt is a front-wheel drive small station wagon, its drivetrain motor is rated at 150 kW (nearly half of Model S),and consumes only 0.26 kWh/mile (30% more efficient than the Model S) under city driving conditions.

The average driving efficiency, usable range, usable capacity of the four existing BEV types, the two upgraded BEVs used in the scenario analysis, and the additional sensitivity study using a 400-mile BEV are tabulated in Table C-4.

BEV feasibility to replace the ICE

I describe the steps involved in determining usable battery capacity, usable range, feasibility criteria to determine if BEV can replace ICE or swap its miles, and the corresponding electrical energy and fuel consumed. I slightly modified the approach for calculating the usable range and instead of using a single aggregate net driving kWh, I binned the distance and the corresponding net driving kWh by city or urban driving, mixed or suburban driving and highway driving. In each of these three driving styles, I calculated three distinct net kWh/mile for every BEV. This was repeated for every ICE and its fuel economy calculations under the three driving styles. The feasibility of BEV to replace an ICE requires that at the start of travel day, there is sufficient energy remaining in the battery to accomplish the ICE gVMT at the same energy intensity (Eq 1), and the corresponding electrical energy and gasoline consumed is expressed using the Equation (2)-(3) respectively. Superscripts indicate one of the three driving styles-city, mixed or highway, $kWh_{nett}^{(.)}$ denotes the net driving kWh/mile ; $mpg^{(.)}$; $ICE_{gvmt}^{(.)}$ indicates the gVMT by the ICE; ; $BEV_{evmt}^{(.)}$ indicates the eVMT by the BEV, $BEV_{day.start}^{kWh}$ denotes the energy in kWh remaining in the battery at the start of travel day

$$BEV_{day.start}^{kWh} \geq \left(kWh_{nett}^{city} \times ICE_{gvmt}^{city}\right) + \left(kWh_{nett}^{mixed} \times ICE_{gvmt}^{mixed}\right) + \left(kWh_{nett}^{hway} \times ICE_{gvmt}^{hway}\right) \quad (1)$$

$$BEV^{kWh} = \left(kWh_{nett}^{city} \times ICE_{gvmt}^{city}\right) + \left(kWh_{nett}^{mixed} \times ICE_{gvmt}^{mixed}\right) + \left(kWh_{nett}^{hway} \times ICE_{gvmt}^{hway}\right) \quad (2)$$

$$ICE^{fuel} = \left(\frac{BEV_{evmt}^{city}}{mpg^{city}}\right) + \left(\frac{BEV_{evmt}^{mixed}}{mpg^{mixed}}\right) + \left(\frac{BEV_{evmt}^{hway}}{mpg^{hway}}\right) \quad (3)$$

Calculating Electrical Energy Required for Driving

In the observed behavior scenario, all relevant information pertaining to the electrical energy required for driving and charging and gasoline consumed is directly available. Drivetrain efficiency depends on driving styles, ambient conditions, auxiliary loads, electric motor and on-board power electronics converter efficiencies[216-219]. To determine the driving net kWh required under different scenarios, I use the Recharge Allocation Factor (RAF). It is a standardized terminology used in the SAE J1634[220] procedure for determining the BEV range measurement and testing. According to the SAE J1634[220], RAF is the ratio of AC kWh required to fully charged the battery to the DC kWh needed for driving in the full depletion test. Equivalently it is the ratio of full recharge AC kWh (FRE) to usable battery energy DC kWh (UBE). Observed and representative RAF values from range measurement and energy consumption tests under different ambient and auxiliary load conditions are summarized in Table C-5.

Table C-5 Observed and laboratory testing estimates[221] of Recharge Allocation Factors

		Lab testing environment conditions					
	Observed	**75°F**	**20°F**	**95°F H**	**20°F**	**95°F**	**BEV Model**
			HVAC OFF		*HVAC ON*		
Leaf	1.171	1.165	1.161	1.151	1.161	1.153	2018 Nissan Leaf
Bolt	1.158	1.133	1.178	1.181	1.178	1.189	2018 Chevrolet Bolt
T60 T80	1.203 1.150	1.147	1.181	1.145	1.183	1.155	2017 Tesla Model S 75D

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