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Behavioral and technology implications of electromobility on household travel emissions

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ABSTRACT

This paper investigates the share of household travel electrified or Utility Factor(UF) and well-to-wheel(WtW) greenhouse gas(GHG) emissions of battery electric vehicles(BEVs) in two-car households. We examine a multiyear travel data collected via GPS loggers from both vehicles (internal combustion engine vehicle-ICE and BEV) belonging to 73 California households:30 Nissan Leaf, 21 Chevy Bolt, and 22 Tesla ModelS.

Results indicate that two distinct substitution patterns moderated by vehicle attributes effectuate diversified outcomes on UF and GHG. Energy efficiency losses due to technology and user preferences counteracts range enabled UF gains offsetting BEV's GHG benefits. Fuel inefficient ICEs could aggravate emissions of longer-range BEV households. Conversely, energy efficiency improvements can augment GHG reduction, but UF decreases.

Maximum UF of 75–80% can be achieved by upgrading to a longer-range BEV. Longer-range performance-oriented BEV upgrade does not improve UF but nullifies 15–30% of emission abatement potential realized by driving their existing BEV instead of ICE.

1. Introduction

The transportation sector emitted 1,900 million metric tons of Carbon-di-Oxide equivalent (MMTCO2e) in the U.S., roughly one-third of total greenhouse gas (GHG) emissions (U.S. EPA, 2018). Close to 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) (U.S. EPA, 2018). In California, LDV segment alone contributed to 28% of the state's total GHG emissions (CARB, 2018). Plug-in hybrid electric vehicles(PHEVs) and battery electric vehicles (BEVs), together addressed as plug-in electric vehicles (PEVs), are being promoted at the state and federal levels to reduce LDV sector emissions and gasoline consumption (UNEP, 2018). Cumulative global PEV stock reached 7 million and new PEV sales exceeded 2.3 million in 2019 (ICCT, 2019, EV-Volumes, 2020). About 315,000 new PEVs were sold in the U.S. in 2019 and 75% (234,000) were BEVs (EV-Volumes, 2020). California is home to 47% of nationwide PEV stock and leads the U.S. in PEV share (8%) of 2019 new car sales (EEI, 2019). However, almost an eightfold growth within the coming decade is needed to meet its 2030 target of 5 million PEVs (CARB, 2017a, Nikolewski, 2019).

Several supply and demand side strategies have been implemented to accelerate BEV adoption by mitigating purchase cost, range

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anxiety, charging infrastructure, and technology awareness barriers (Block et al., 2016, Egbue and Long, 2012, Singer, 2017, Zhou et al., 2016). These encompass demand side financial incentives for BEV and electric vehicle supply equipment(EVSE) purchase, (Narassimhan and Johnson, 2018, Sierzchula et al., 2014, Zhou et al., 2015), technology forcing Zero Emission Vehicle (ZEV) mandates (Contestabile et al., 2017), performance standards like the Low Carbon Fuel Standard (LCFS) (CARB, 2009), Corporate Average Fuel Economy/Consumption (CAFE/CAFC) targets, and GHG standards (U.S. EPA, 2019). 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 (Lieven, 2015). 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. This depends on the interactions between driving and charging behavior, technology attributes (range, vehicle specifications) and user preferences.

A compelling aspect often overlooked in BEV GHG assessments is the household(HH) context. According to the *hybrid household hypothesis* (Turrentine and Kurani, 1995, Kurani et al., 1994), BEV early adopters are more likely to be in multi-car households. More recent studies report that nearly half of BEVs belong to multi-car households (Tal et al., 2020b). Household factors like size, number of drivers, socioeconomics, and demographics affect long-term purchase decisions, intra-day vehicle usage, and household travel demand (Ding et al., 2017). Depending on travel needs, individual preferences, operating costs, charging access and opportunities, electric vehicle miles traveled (eVMT) by the BEV has cascading effects on gasoline VMT(gVMT) by other household vehicles. Two contradicting hypotheses are at the root of most of the research on BEV usage and performance. The first argues that limited range and infrastructure gaps prevent BEV users from fully using their range and may shift usage to ICEs in a household. The second hypothesis asserts that the lower cost per mile of driving a BEV will shift miles from ICEs to BEVs and account for a higher share of HH VMT than the original share of ICE the BEV eventually replaces. These interrelationships highlight the importance of household context and appropriate metrics for BEV GHG assessments. In the policy domain, chief metrics are GHG (gCO2e/mile), Utility Factor(UF), and electric vehicle-miles traveled(eVMT). Fraction of VMT electrified using off-board grid electricity is called the UF. The role of electricity as a transportation fuel is communicated through the UF and eVMT is defined as the miles driven by off-board grid electricity.

This paper draws attention to a research area scarcely studied in extant literature–actual and potential BEV utilization in multi-car households and its consequences on household travel electrification and emissions. We examine actual BEV usage patterns based on a rich multiyear observational travel dataset of 73 ICE-BEV California households–30 Nissan Leaf, 21 Chevrolet Bolt, and 22 Tesla Model S. Using scenario analysis, impacts of potential BEV usage on household UF, GHG, and fuel savings are quantified.

1.1. Household travel emissions and electrification potential

Various mechanisms underpinning household travel GHG can be informed using the ASIF (Schipper and Marie-Lilliu, 1999) identity by expressing GHG as the product of 4 variables: *A*(activity or VMT), *S*(mode share), energy intensity(*I*), and fuel (*F*) carbon intensities. Household travel emission is the sum of ICE driving emissions from gasoline consumption and emissions due to electricity required for charging the BEVs. Total household travel demand, share of ICE gVMT and BEV eVMT, and energy intensities are susceptible to household preferences, on-road conditions (congestion, grade, terrain), driving styles (urban, suburban, highway), vehicle characteristics (size, power, weight), and powertrain efficiencies (Yuksel et al., 2016, Elgowainy et al., 2018). The quantity and quality of ICE miles (for example fuel efficient cruising miles or inefficient start-stop city driving miles) substituted affects the BEV energy consumption, volume of gasoline displaced, and HH GHG. If only the BEV is included, much of the insights on household travel demand and purpose of BEVs is lost. It is difficult to ascertain if there is any room for further abatement, compare across households and different BEV types to better understand the ties between travel needs, range, and GHG.

1.2. Literature Review

Insights gleaned from prior works on BEV usage and their GHG abatement potential depend on type of survey (cross-sectional or longitudinal surveys), methodology (stated or revealed preferences), instrumentation(online survey or data loggers), and sampling (mainstream ICE users, prospective BEV buyers, or existing BEV users). In the context of household travel electrification, survey design (before and after BEV use or post BEV use only), unit of analysis (vehicle level or household level), and information collected (duration and spatiotemporal resolution of data) are very important.

For any BEV usage assessment, daily eVMT and electrical energy consumed are prerequisites. Self-reported trip diary information or in-use data collected via loggers from ICEs in household travel surveys are often used as proxies to assume typical driving and dwelling patterns of BEVs (Chajka-Cadin et al., 2017, CalTrans, 2013, Pasaoglu et al., 2014). These are widely adopted to model BEV adoption (Javid and Nejat, 2017) and market penetration (Zhang et al., 2020, He et al., 2016, Tamor et al., 2013). Energy consumption is determined using test cycle values or can be estimated by simulating naturalistic drive cycles (Ji and Tal, 2020). Emissions are calculated under different scenarios for driving and charging requirements, electricity generation mix, and policies (He et al., 2019, Desai et al., 2020). Increase in BEV adoption facilitated a better understanding of early adopter driving and charging behavior using stated choice and adaptation experiments (Figenbaum and Nordbakke, 2019, Haustein and Jensen, 2018, Lee et al., 2019). Concerted efforts have been undertaken over the past decade in observing real-world BEV usage via vehicle telematics systems or electronic logging devices(ELD) through field trials and fleet demonstrations (INL, 2015, Weldon et al., 2016, Xydas et al., 2016, Sun et al., 2015, GEOTAB, 2020b).

Extrapolating vehicle-level driving and charging preferences on to the household level poses additional challenges. First, early adopter or early majority segment of BEVs are likely to be multi-car households (Kurani et al., 1996, Turrentine and Kurani, 1995, Golob and Gould, 1998). Ignoring the *other car* provides a limited and probably biased appraisal of the BEV's role. Second, BEV ownership is influenced by socio-demographics (Gu et al., 2020), built environment (van de Kamp, 2020, Westin et al., 2018), psychological dynamics governing user preferences (Axsen et al., 2015, Li et al., 2017), and the policy impetus (Contestabile et al., 2017, Gubman et al., 2016, Langbroek et al., 2016, Lieven, 2015). Household vehicle ownership may also change in response to mobility, life-event, or aspirational stressors (Oakil et al., 2014). Salient traits of BEVs such as range anxiety, access to charging infrastructure, high capital cost and low running cost affects BEV's share or even the total household travel demand (Archsmith et al., 2017, Huwe and Gessner, 2020, Seebauer, 2018).

Adoption feasibility of BEVs(60–120 mile range) is evaluated using multi-day in-vehicle GPS travel data of ICEs from 255 Seattle households (PSRC, 2008) in (Khan and Kockelman, 2012). The second-car or the one with the lower VMT in multi-car households is replaced by the BEV. The candidate BEV's range is determined based on daily VMT and varying cutoffs on the percentage of days VMT exceeds the range. Authors report that a 100-mile BEV can replace 50% and 80% of single and multi-car households respectively, provided they use another vehicle or mode up to 4 days/year. Another study using the same dataset adopts an optimal deployment strategy wherein households maximize travel electrification by using the BEV for the longer of the trips (in case of multi-car households) whenever possible and for short-trips only when necessary (Tamor and Milačić, 2015). Their results suggest 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 (Tamor and Milačić, 2015). A heuristic Household Activity Pattern Problem with Electric vehicle(HAPPE) model is developed based on California Household Travel survey [CHTS] (CalTrans, 2013) in (Khayati and Kang, 2019). Authors report that up to 54% of household travel can be electrified using an 80-mile range BEV.

Seven-day trip diary of 6,000 vehicles from the German household travel survey and a week to 2 month in-use GPS data of 400 conventional vehicles operating in Sweden are combined and analyzed to determine the technical and economic viability of BEVs in (Jakobsson et al., 2016a). Authors report 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). In related works, the number of days daily VMT exceeds the range or *Days Requiring Adaptation (DRA)* is used as an indicator to examine the implications of BEV range in single and multi-car households (Jakobsson, 2019, Jakobsson et al., 2016b).

A mixed integer quadratically constrained program to maximize BEV driving is formulated using 1–3 months of GPS logger data from 64 commuter households with 2-cars in Sweden (Karlsson, 2017, Karlsson, 2016). The boundary conditions for BEV substitution are determined by the overlapping (and non-overlapping) driving duration of both cars, use-cases (*confinement, extension, backup, or flexibility*), substituted car (*main or second-car),* BEV range, and charging rates. The substitution potential is translated into total cost of ownership(TCO) gains for every household for various battery ranges and charging rates, and any unfulfilled driving incurs a fixed cost penalty. Authors report that the net present value of BEV flexibility varies between $2000 and $11000 and the average value of flexibility is estimated to be $6700, which is ten times more than the value of BEV confinement ($700).

A sub-sample of 20 out of the 64 two-car households referred in (Karlsson, 2013) subsequently participated in a BEV trial. In this study, one of the ICEs was replaced by a 2015 Volkswagen eGolf (75-mile range). Travel data of both vehicles were collected using GPS loggers before (pre BEV trial) and after BEV introduction (post trial). Household mobility patterns and mileage allocation between the ICE and BEV are investigated in (Karlsson, 2020). Substitution strategy, use-cases, and economic valuation followed author's earlier works (Karlsson, 2016, Karlsson, 2017). Overall, BEV share of total household travel was 46.7%, about 2% more than the car it replaced. Analysis shows that the share of household travel electrified could be improved by up to 60% compared to BEV's actual share of household travel (Karlsson, 2020).

The effect of adding and encouraging the use of a 90-mile range BEV (Peugeot iOn, Citroën C-Zero or a Mitsubishi ImiEV) for three months in 100 Denmark households is examined in (Jensen and Mabit, 2017). Authors develop a mixed logit model to identify factors that influence BEV or ICE selection for home based journeys and a mixed non-linear regression model to estimate daily VMT. Results indicate BEVs are preferably used for short-distance weekday morning trips in comfortable weather, whereas their usage reduced during weekends.

Though perceived as a transitional and intermediate technology, PHEVs also plays a strategic role in LDV electrification and GHG mitigation. Households with long-distance driving needs, inability or very low tolerance for range anxiety and inconvenience, insufficient home and or workplace charging access, and lower willingness to pay for BEVs are some market segments which the PHEVs can fill (Ji and Tal, 2020). Furthermore, longer range PHEVs like the Chevrolet Volt (35-miles or more) can electrify as much as a Nissan Leaf (100-miles or less) in two-car households (Mandev et al., 2019). If optimized for maximum flexibility, BEVs offer twice as much value ($1000/year) in flexibility and have lower TCO than PHEVs (Björnsson and Karlsson, 2017).

1.3. Research gaps

Prior research clearly advocates the need to have a realistic representation of BEV usage to increase their usefulness to policymakers. Relevant multi-car household studies mainly focus on BEV market acceptance and its sensitivity to range, threshold for inconvenience, and whether the primary or second car is replaced by fusing cross-sectional household travel surveys and observational travel data of mainstream ICE users (Tamor and Milačić, 2015, Tamor et al., 2013, Khan and Kockelman, 2012, Kang et al., 2017, Javid and Nejat, 2017, Greaves et al., 2014). Using actual car movement GPS data of all household vehicles, flexible replacement strategies and resulting economic gains for different BEV ranges and charging rates have been examined (Karlsson, 2013, Karlsson, 2017, Jakobsson et al., 2016a, Björnsson and Karlsson, 2017). Desirable experimental settings of these studies notwithstanding, insights and conclusions drawn from ICE travel behavior data might not represent driving and charging behavior of actual BEV users.

Current literature on actual BEV usage drawn from observational travel behavior data of the entire household is limited. Other than this manuscript, very few studies examine actual BEV usage in multi-car households by collecting travel data from both household vehicles using GPS data loggers (Jensen and Mabit, 2017, Karlsson, 2020, Mandev et al., 2019, Tal et al., 2020b). This study differentiates from existing literature on both the revealed behavior of BEVs and their emission impacts in multi-car households by addressing these gaps:

(i) *Performance assessment metrics*: Quantifying BEV feasibility and substitution potential is necessary but not sufficient. Different evaluation criteria are needed to comprehend these days and miles to uncover potential tradeoffs between electrification and its GHG consequences. Three performance metrics are employed: Utility Factor, per-mile well-to-wheel(WtW) GHG emissions (gCO2e/mile), and annual fuel savings in Gasoline Gallons Equivalent(GGEq).
(ii) *Driving style heterogeneity*: 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. These could vary across households with different BEVs, or even among households with the same BEV. These are magnified when we consider inter-household ICE driving energy intensity variations. From a driving efficiency and energy consumption perspective, ICEs and BEVs are suited in complementary driving situations. Start-stop city driving is well suited for BEVs because of their regenerative braking capabilities, but in such conditions the ICEs operate below their optimal efficiency (Borlaug et al., 2020a). In contrast to prior works that consider only the absolute miles, the allocation of household travel between the BEV and ICE by daily driving distances and driving style (city, mixed, highway) is quantified in this study. This reiterates the importance of examining on-road efficiency and emission factor differentials of BEVs and ICEs together at the household vehicle portfolio level. This would be completely lost if we look at only the BEV or ignore the relative energy intensity variations.
(iii) *Granularity of revealed behavior*: Travel data collected from short-duration field trials may not be adequate to adapt and utilize the full BEV range. Evidence suggests that on average 98 vehicle ownership days and 1500 VMT over 62 driving days are required for a 156-mile range BEV driver to maximize range utilization (Pichelmann et al., 2013). In our study, entire household's travel and recharging behavior is monitored for a year. Observing actual usage for a year captures the full spectrum of trip and VMT distribution. This is especially valuable since long-distance trip related range anxiety is a major obstacle to mass market BEV adoption (Figenbaum and Nordbakke, 2019).The duration and resolution of data collection better characterizes real-world energy consumption.
(iv) *Evolution of BEV attributes*: Limited BEV models by range and specifications are considered in previous observational BEV usage studies. This precludes cross-household comparisons among BEVs with comparable range but disparate specifications, drivetrain architecture, and efficiencies. Compared to existing BEV usage studies that observe and analyze only 1-type of BEV, our study includes diverse BEV specifications (e.g., size, electric drive ratings, range, and interior) reflecting market trends,

Table 1
Socioeconomics, demographics, and vehicle characteristics sampling comparisons between this study and 2017 National Household Travel Survey (TSDC, 2017, U.S. FHWA) 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%)
Education	Less than a high school graduate	10204(18%)	1(1%)
	High school graduate	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%)
Number of vehicles	0	966(7%)	
	1	4084(31%)	
	2	4490(35%)	73(100%)
	3 or more	3505(27%)	
ICE class	Car	56%	34%
	Light truck	44%	66%
Average annual VMT	ICE	9501	8645
	BEV	10,503	12,737

internalized purchase, and usage preferences of current early adopters in California. Data collection spans 25,000 days across 73 households, and three distinct BEV models with varying range and vehicle specifications are considered.

This paper scrutinizes revealed BEV usage and evaluates the consequential environmental impacts of potential BEV usage. A highly resolved travel behavior dataset collected via on-board diagnostic port (OBD) GPS enabled 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 is analyzed. Potential BEV usage is evaluated given a set of behavior and BEV attribute modification scenarios. Six scenarios were selected to capture the individual and combined effects of travel day vehicle selection, overnight full charging at home, and whether the household kept its current BEV attributes or replaced it with a *longer-range efficiency* or *longer-range sportier performance-oriented* BEV. Ensuing impacts on household travel electrification, emissions, and fuel savings are systematically quantified. Comparative assessments with revealed usage are performed across different scenarios and BEV types through the chosen metrics-Utility Factor, per-mile GHG, and fuel savings. Research inquiries and insights shed light on the relationships between household preferences and vehicle attributes, and their manifestations on the performance metrics.

2. Data and methods

The principal data source is the Advanced Plug-in Electric Vehicle Travel and Charging Behavior project or the "*eVMT project*" (Turrentine and Tal, 2015, Tal et al., 2020b). This project was started in 2015 to understand how current PEVs are being used on a day-to-day basis within the context of household travel in California. This project includes an online survey followed by a yearlong data collection from a sub-sample of respondents who expressed interest in participating in the logger study and planned to keep their PEV for at least a year. Data loggers with GPS capabilities were installed in the OBD-II port of all household vehicles belonging to these sub-sample of respondents. Online survey and logger data were collected as part of a larger research project with a much broader set of research questions besides the ones addressed in this paper. The eVMT data collection was devised for purposes rooted in the revealed usage patterns post-PEV purchase. The analyses presented in this paper uses online survey and observational travel data collected from 73 two-car (single ICE and BEV) California households that took part in the eVMT project.

2.1. Online survey

Online survey of current PEV owners who purchased or leased their PEV in the last 4 years was conducted between June 2015 and July 2017. Participants were randomly sampled from the Clean Vehicle Rebate Project (CVRP) database (CSE, 2020) and vehicle registration records. 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 (Cox Automotive, 2017, Singer, 2017) and 50% more completed responses than international studies (Giffi et al., 2011). Nearly 12,396 of the respondents indicated their willingness to take part in the data logger study. 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 used to recruit participants. Due to logistical concerns, travel overheads associated with logger installation and uninstallation process, convenience sampling strategy was employed when needed. The stratification was based on the territorial coverage of the five major utility companies in California. Only limited knowledge about the household vehicle ownership prior to BEV purchase is available–year, make, model of the vehicle BEV replaced and purchase reasons (added the BEV, replaced an ICE, replaced a similar or different BEV). Our survey instrument and the follow-up data collection tasks do not categorize household vehicles into *main or primary car* and *second car* by VMT or based on holdings before and after BEV purchase. A pre-post BEV usage comparative study is not possible and thereby excluded by virtue of survey design and data gathered.

2.2. Sample representativeness and limitations

Select sociodemographic and economic indicators observed in this study with California statistics (U.S. FHWA, TSDC, 2017, CSE, 2020, Cox Automotive, 2017, Liao et al., 2017) are presented in Table 1.

Sampling comparisons with the CVRP dataset and coverage by utility is summarized in Appendix Table A1. Overall, observed BEVs represent 75% of the models that were issued the CVRP rebate during 2015–2020 and comparable in terms of proportional coverage by electric utility, Table A1. Compared to the NHTS-CA sample, the over-representation of participants by home ownership, gender, income, and education is due to the socio-demographic profile of BEV early adopters (Lee et al., 2019, Johnson and Williams, 2017, Nicholas et al., 2017). 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. Forty-eight households (66%) have light-truck (LT) segment ICE (Table 1 and Fig. A1). Sampling differences between this study and NHTS-CA dataset in terms of household size, vehicle count, and number of drivers is due to the scope of this study. Appendix Table A2 provides a snapshot of charging accessibility and incentives availed reported by the data logger study participants.

Table 2
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	10,841	1089	9258	386	2471	20,099
Bolt	21	1303	12,470	945	9625	367	2248	22,095
T60	12	952	17,236	1097	7356	388	2049	24,592
T80	10	866	13,507	902	6213	308	1768	19,720
Total	73	88,899	929,795	74,700	631,126	27,040	163,599	156,091
	Number of charging sessions by charger type(CEC, 2018, Kettles and Raustad, 2017, SAE, 2017)			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	20,637	18,400	2237	271,852	231,194	38,731		

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.

Over 90% of the participants (68 out of 73) have access to home charging. Fifty-three (80%) out of the 73 HHs availed the Clean Air Vehicle decals[1].

Small sample size, external validity, and generalizability limitations of our data must be acknowledged. Due to the survey design, data collection period, and scope of this study, self-selection bias and correlation among key sociodemographic and economic indicators is innate. It is infeasible to control for every correlation from an analytical perspective. Resource constraints and logistics of data logger installations dictated the number and type of BEV households eventually selected and analyzed. Given these circumstances, no attempt is being made to project the insights gathered from this study on the behavior and preferences of California or nationwide BEV users. As such, the results presented in this paper should be comprehended within the early adopter BEV market segment from a transferability perspective rather than for generalizing cross-population.

2.3. Driving and charging data from loggers

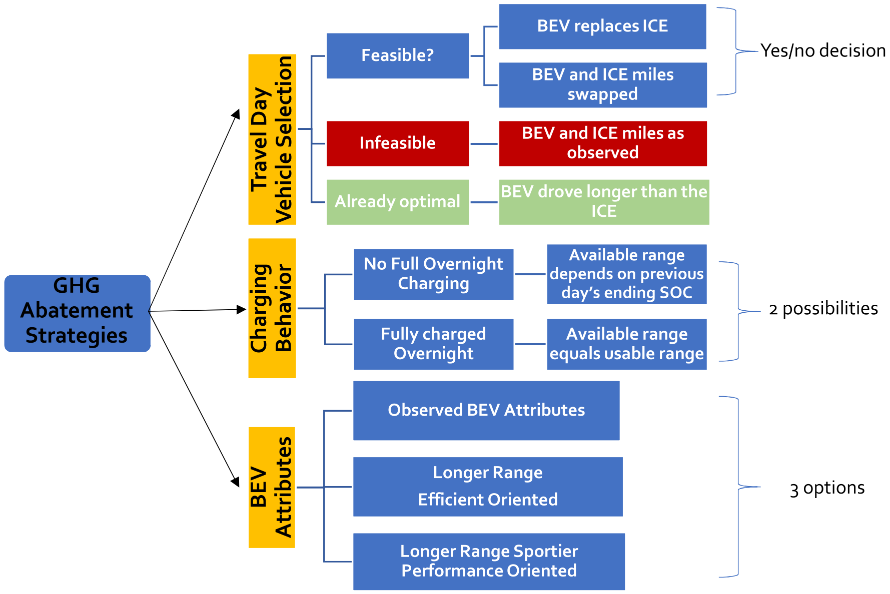
In the sub-sample of 73 households, GPS enabled data loggers were installed in the OBD-II port of all vehicles belonging to the household (146 vehicles in total). The raw data relayed by the electronic control module is monitored via OBD at 100 Hz and temporarily stored in the data logger's flash memory at 10 Hz. Logger data is transmitted via cellular network to a secure FTP server and downloaded for analysis. Resource and logistical constraints on costs, flash memory, and secure server storage requirements, backend data validation, and quality control complexity are normal in vehicle telematics data collection. Data acquisition, transmission, storage, and post processing rates also varied by vehicle type, model and year, compatibility between vehicle's OBD port, logger hardware and firmware version (FleetCarma, 2019, GEOTAB, 2020a, Francfort, 2016).

2.3.1. Data curation and post-processing

Vehicle speeds, GPS data, onboard temperature, date and time stamps, DC currents, voltages, engine rpm, starting, and ending SOC, AC currents and voltages, and cumulative charged/discharged energy were collected. Except for SOC and GPS which were sampled at 10 Hz, rest of the parameters were collected at 1 Hz. Additional flags to denote key-on/off, vehicle plugged or not, charger level, odometer readings were used for validation.

Data was collected between June 2015 and November 2019, spanning 25,000 days. On average, every household was monitored for 325–374 days depending on the BEV type. The aggregate annualized data includes 164,000 household trips (89,000 BEV and 75,000 ICE trips) and 1.56 million household VMT (930,000 eVMT and 630,000 gVMT by the ICE), Table 2. During the study period, 27,040 gallons of gasoline and 272 MWh of electricity were consumed, Table 2. Average fuel economy of ICEs observed varied from label estimates by −17% to 10% (Refer Appendix Fig. A2). Average usable range of observed BEVs was 5–15% less than the window sticker label range (Appendix Fig. A3 and Table A3).

[1] California Department of Motor Vehicles issues Clean Air Vehicle (CAV) decals to qualified vehicles meeting emission standards that allows single occupancy use of High Occupancy Vehicle(HOV) or carpool lanes.



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

Fig. 1. Methodological framework, GHG abatement strategies, scenario selection and nomenclature. Pairwise [1,2] imply existing BEV attributes, [3,4] existing BEV upgraded to longer-range efficiency oriented BEV, [5,6] existing BEV upgraded to longer-range sportier performance- oriented BEV. Odd numbered scenarios indicate travel day vehicle selection with available range less than usable range. Even numbered scenarios denote travel day vehicle selection with available range equaling usable range due to full overnight home charging.

2.4. Methodology description

Substitution and emission reduction benefits of BEVs depends on the interactions between–household preferences on vehicle selection and trip allocation; day-to-day driving and charging behavior; and BEV attributes. Travel patterns revealed *ex post* from the logger data serves as the basis for understanding current usage patterns of BEVs and ICEs. Six salient scenarios to characterize one or more modifications to the observed driving and charging behavior, and BEV attributes were selected. The purpose of developing these six scenarios is to identify opportunities to increase BEV usage and its effect on UF, GHG, and net fuel savings. The extent to which BEVs replace ICEs in a household is bounded by the set of possible option(s) covered by the scenarios. These are specific and very sensitive to the experimental design and problem setting. Three GHG mitigation strategies were considered–Travel day vehicle selection, fully charged overnight at home, and BEV attribute upgrade, Fig. 1.

Travel day vehicle selection strategy captures shifting high carbon intensity gVMT to low carbon intensity eVMT. To ensure the utility of BEV is maximized, this is applied on a subset of days when ICE drove longer than the BEV (including days when only the ICE was used) and available range suffices to accomplish the ICE gVMT. Usage patterns on the following days are left unchanged–days when only the BEV was driven, or BEV drove longer than the ICE when both were used; and days when it is infeasible to replace or swap ICE miles due to range inadequacy. *Replace* and *swap* are used to distinguish days when only the ICE was used and when both vehicles were used, respectively.

Usable battery capacity corresponding to 100% SOC is calculated by interpolating charged SOC and charged kWh for every BEV. Usable range is estimated from usable battery capacity and the electrical energy consumed per mile. Available range is obtained by proportionally scaling the usable range by travel day starting SOC. 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. The *charging behavior strategy* is an insight into what would happen if all these BEVs are fully charged 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 considered is *BEV attribute modification*. Three possible options were included depending on whether: i) households keep their existing BEV as it is; ii) households decide to replace their existing BEV and upgrade to a longer-range efficiency oriented BEV*(LREffi)*; or iii) households upgrade to a longer-range sportier performance oriented BEV *(LRPerf)*. One or more of these GHG abatement strategies lends itself to a possible of these six scenarios, excluding the reference case.

Obs_Beh: Baseline reference scenario. Observed driving and charging behavior, and travel day vehicle selection. Available range is calculated by scaling the usable range proportionally to the previous day's ending SOC.

[S1] VehSelect: Household drivers select their current BEV instead of the ICE, provided available range at the start of travel day suffices to accomplish the ICE miles.
[S2] VehSelect FullChg: S1 VehSelect plus BEVs fully charge overnight at home. Available range at the starting of travel day is their full usable range.
[S3] VehSelect LREffi / [S4] VehSelect LREffi FullChg: Follows S1 VehSelect / S2 VehSelect FullChg with a *LREffi BEV*.
[S5] VehSelect LRPerf / [S6] VehSelect LRPerf FullChg: Follows S1 VehSelect / S2 VehSelect FullChg with a *LRPerf BEV*.

2.5. Methodological and parametric assumptions

2.5.1. Estimating BEV emission reductions

The nett environmental benefits of BEVs depend on its emissions relative to the replaced vehicle emissions and the system boundary for GHG quantification. There is a consensus among researchers on choosing a well-to-wheels(WtW) or cradle-to-gate (C2G) approach to account for the GHG emissions from vehicle and battery manufacturing, assembly, disposal, and recycling (Nykvist et al., 2019, Elgowainy et al., 2018, Ellingsen et al., 2016, Hawkins et al., 2013, Archsmith et al., 2015). Emission benefits of BEVs varies depending on regional electricity generation mix and ambient conditions (Elgowainy et al., 2016, Yuksel et al., 2016, Nealer and Hendrickson, 2015, Yuksel and Michalek, 2015, Desai et al., 2020). Though the manufacturing phase might introduce additional GHG, in certain instances, use phase GHG could be close to zero if charged from completely renewable sources, for example Tesla household with solar panels and Powerwall (Tesla, 2019). We used WtW emission factors provided by the California Air Resources Board (CARB, 2019a, CARB, 2017b)–11405.85 gCO2e/gallon for gasoline and 378.54 gCO2e/kWh for electricity. These emission factors were developed using the CA-GREET model (CARB, 2019b, CARB, 2017c). To ensure consistency with the official values used by the administering agency in their GHG Reduction Fund programs, only the WtW GHG is considered.

Very limited information on household vehicle holdings prior to survey participation is available. Reasons for BEV purchase reported in the survey included replacing an ICE (56/73 households), replacing a BEV (9/73), and eight households added a BEV as a second car. Only 41 of the 65 households that purchased the BEV to replace a pre-existing vehicle had valid survey responses to the year, make, and model of ICE or BEV replaced by the BEV. A simplified before/after BEV emissions and fuel consumption of these 41 households is presented in Appendix. Household emissions and annual fuel consumption reduced on average by 40–50% after BEV purchase relative to pre BEV purchase levels (Table A5 and Fig. A4). Due to incomplete information and parity considerations, a controlled pre/post BEV purchase decision setting to estimate their net GHG impacts is incompatible. Moreover, as mentioned in the logger data and online survey sub-sections, because of survey design, a pre/post BEV comparison is beyond this study's scope. Substituted miles and resulting gasoline displaced are expressed relative to the existing ICE. A California specific study conducted recently quantified the emission abatement potential of BEVs and the subsidy costs incurred (Muehlegger and Rapson, 2020). The average fuel economy of ICE replaced by BEV was between 20 and 22.5 mpg. Fleet average fuel economy of ICEs (73 households) analyzed in this study is 23.3 mpg. The fleet average fuel economy of previous ICE (replaced by BEV) based on complete information (41/73 households) was 24.9 mpg in this study. The estimated GHG reductions presented in this study would still be a conservative estimate because the replaced ICE's fuel economy in this study is higher than fuel economy of replaced ICE reported in related state-wide assessments (Muehlegger and Rapson, 2020).

2.5.2. Travel day available and usable range

To determine the feasibility of BEV to replace ICE or swap its miles, and the corresponding electrical energy and fuel consumed, the approach for calculating the usable range was slightly modified. Trip distances are binned by speed intervals into three driving styles: *city or urban driving (0-45mph], mixed or suburban (45–60 mph], and highway driving styles (60mph or more)*. The granularity of the speed-time trace data enables distance binning by speed in 5mph intervals. Distances, fuel, and electrical energy consumed in the individual 5mph speed bins are then aggregated to the chosen speed intervals resembling the driving styles. These *"city", "mixed",* and *"highway"* driving styles are not inferred by geo-coding trip-level GPS data onto the physical road network. These are based on speed binning by post-processing and strictly used to characterize different driving energy intensities.

In each of these driving styles, three distinct net kWh/mile for every BEV were calculated. Likewise, fuel economy under different driving styles is calculated for every ICE. Each household has a driving style specific and overall fuel economy and electrical energy consumption values. Effectively, driving energy intensity and efficiency which could vary among households with the same BEV and across households with different BEVs is accounted. The feasibility of BEV to replace an ICE is conditional upon sufficient energy remaining in the battery at the start of travel day to accomplish the ICE gVMT at the same energy intensity and driving styles (Eq (1)). This condition is checked, and the corresponding electrical energy and gasoline consumed is evaluated using the Eqs. (2)–(3) for every travel day. Gasoline consumption is derived from the fuel rates and vehicle speeds and driving style specific fuel economy in miles per gallon(mpg) is calculated from gVMT and fuel consumed in the respective driving styles. Likewise, for driving style specific per-mile electrical energy consumption. Superscripts show one of the three driving styles-city, mixed or highway, $kWh_{nett}^{(.)}$ denotes the net driving kWh/mile; $mpg^{(.)}$; $ICE_{gvmt}^{(.)}$ shows 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.

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

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

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

2.5.3. Calculating electrical energy required for driving

In the observed behavior scenario, 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 (U.S. DOE, 2016, Thomas, 2014, Kugler et al., 2016, Good.D, 2017). To determine the driving net kWh required under different scenarios, the Recharge Allocation Factor (RAF) is employed. It is a standardized terminology used in the Society of Automotive Engineers (SAE) J1634 (SAE J1634, 2017) procedure for BEV range measurement and testing. According to the SAE J1634 (SAE J1634, 2017), RAF is the ratio of AC kWh required to fully charge 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 under different ambient and auxiliary load conditions is summarized in Appendix Table A4.

2.5.4. Spatiotemporal aspects of travel-day vehicle selection

An all -or- nothing substitution between BEV and ICE miles at a daily level is used. This perfect foresight on travel day VMT is acceptable considering that irrespective of which vehicle(s) were driven, daily travel needs will be met. Since both vehicles are monitored, any short-run elasticities with respect to prices, traffic, climate, and respondent socio-economic and demographic indicators are implicitly accounted in their actual VMT changes. Both vehicles are assumed to start their daily mission from home. Simplification of locational constraints has a negligible impact in this study. This relaxation mostly concerns when vehicle switching is allowed on certain days in the scenario analysis but observed GPS data shows otherwise. Haversine distances based on travel day starting and ending GPS data of both vehicles with respect to each other, and in relation to their home location were calculated. It was found that only on 3% of time when both vehicles were driven, observed travel patterns contradicted the assumption. Moreover, 99.5% of the time when only the ICE was driven, BEV was parked at home.

2.5.5. Charging and BEV purchase preferences

Observed charging behavior is modified to include the possibility of fully charging overnight at home. Additional charging opportunities within-day at workplace or public charging, including fast charging from trip level data and dwelling patterns is excluded for couple of reasons. Interactions with charging infrastructure depends on BEV user motivations, range, accessibility by location, charging cost and tariff design, charger capacity, and coverage density (Hardman et al., 2018, Lee et al., 2020, Nicholas et al., 2019). Effect of public charging, particularly DCFC on travel demand depends on many factors – maximum acceptance power of the on-board charger (Nicholas and Hall, 2018), existing DCFC coverage and its relative value over standard L1/L2 charging (Neaimeh et al., 2017), trade-off between battery sizes and DCFC network expansion (Funke et al., 2019a, Gnann et al., 2018), and household travel allocation preferences and needs (Tamor, 2019). Various charging behavior strategies could be expressed by superimposing user-defined charging scenarios, subject to travel data and operational considerations. Specific to this study, total kWh charged is of primary interest compared to cost of charging, charger level, and location, since we use state average emission factors for electricity as discussed in the GHG quantification and system boundary subsection. Given these design, behavioral, and technological considerations, and the array of possibilities regarding DCFC and public charging broadly, we included only overnight home charging. To achieve a balance between capturing charging preferences and incorporating realistic charging scenarios supported by available data, only full overnight home is considered. This is coherent with the daily time-scales of *travel day vehicle selection strategy* and justifiable since 90% of the households (68 out of 73 households) in this study have home charger access (Refer Appendix Table A2) and considering that home charging is the most preferred charging location (Funke et al., 2019b, Nicholas et al., 2019).

The last set of assumptions pertains to *BEV attribute modifications*–households keep their existing BEV or upgrade to one of the two following options–*longer range efficiency (LREffi)* or *longer range sportier performance oriented BEV (LRPerf)*. Multidimensional factors (Mukherjee and Ryan, 2020, Lee et al., 2019, Liao et al., 2017) influence long-term purchase preferences. Day-to-day operational costs, convenience, trip purposes, and activity patterns affect daily usage. It is beyond the scope, nor is the aim of this study to simulate a matrix of charging choices for different BEV ranges by power levels and locations, and its impact on long-term and day-to-day economics. A straightforward approach that combines technology enabled performative aspects without conflating or diluting household driving and charging preferences is employed. This helps in understanding how the GHG benefits and substitution potential of a BEV household (e.g., Nissan Leaf) changes, *ceteris paribus*, if upgraded to a *LREffi* or *LRPerf*.

From a limited consideration of income, education, dwelling type, and home ownership criteria, majority of households (Ref. Table 1) align with typical traits of Tesla household: Male, homeowner, and earns more than $100,000 (Hedges&Company, 2019, EVUnite, 2020). Though this is a coarse approximation using a high end BEV adopter as an example, scenarios are not drawn based on mainstream ICE or any non-BEV household travel patterns, demographics, and their respective internalized preferences such as in

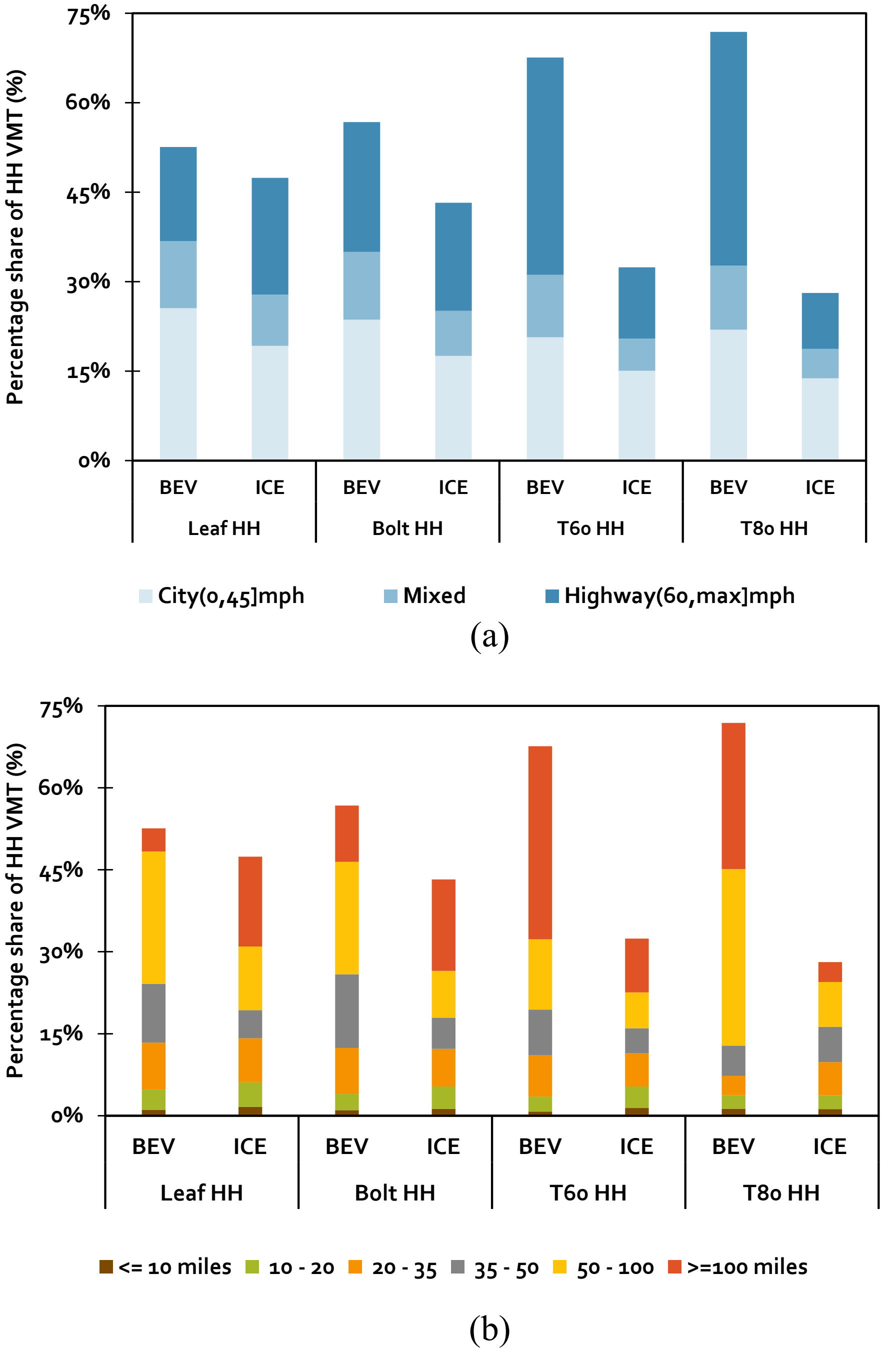


Fig. 2. Descriptive driving summaries and contribution to GHG. (a) Share of household VMT by vehicle used and driving style; (b) Share of household VMT by vehicle used and daily driving distances.

related studies (Björnsson and Karlsson, 2017, Greaves et al., 2014, Kang et al., 2017, Karlsson, 2017, Khan and Kockelman, 2012, Khayati and Kang, 2019, Pearre et al., 2011, Tamor et al., 2013, Tamor and Milačić, 2015). Scenarios selected in this study are applied to 2-car ICEBEV households with similar demographic and socioeconomic profiles within the same geographical region and subject to the same policies.

3. Results

Select insights on observed driving behavior, UF and GHG profiles are presented followed by the scenario analysis results.

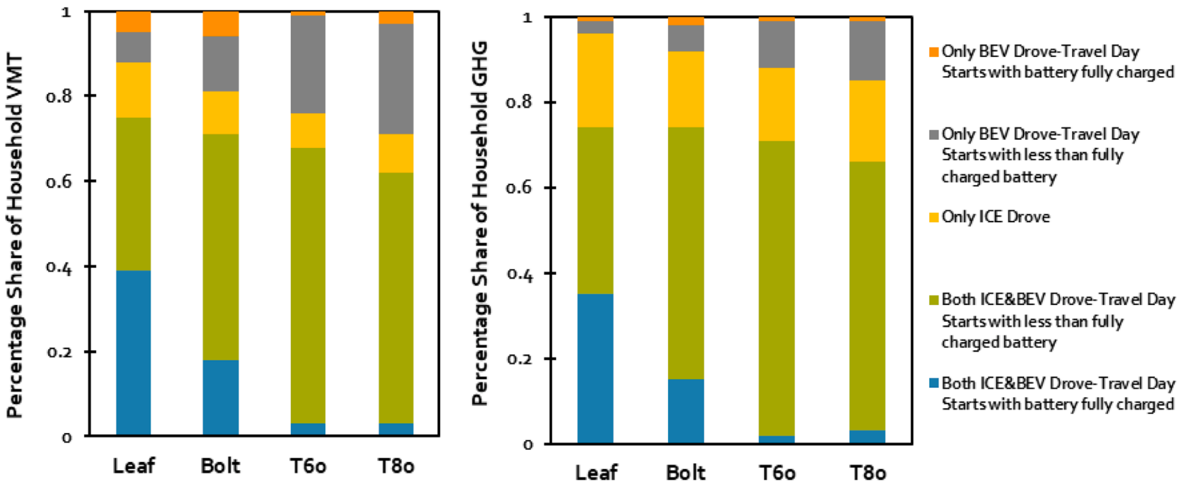


Fig. 3. Share of household VMT by vehicle(s) used and travel day starting SOC and corresponding share of household GHG.

3.1. Driving summaries

Fig. 2(a)-(b) depicts the share of HH VMT by vehicle, daily VMT and speed intervals. In Leaf and Bolt HH, BEV and ICE utilization by distances and speeds are relatively similar. Average ICE and BEV trip distances are comparable within Leaf (8 miles) and Bolt HHs (10 miles). Bolt HH UF is only slightly better or even comparable to that of Leaf HH, though Bolt's usable range (238-miles) is more than twice the usable range of a Leaf (87-miles). Fig. 2(b) 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 most of the daily travel 100 miles or more. Teslas accomplish almost 40% of their travel at highway driving styles (60mph+), almost twice that of the Leaf and Bolts.

It is not surprising that majority (60–75%) of the HH VMT and GHG is due to both vehicles being driven (Fig. 3**)**. However, close to 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 minimized as is and further GHG mitigation is not possible because only the BEV was driven. As range increases, the number of days and thereby the share of HH VMT by the BEV alone also increases from 7% in Leaf HHs to almost 25% in T80 HHs.

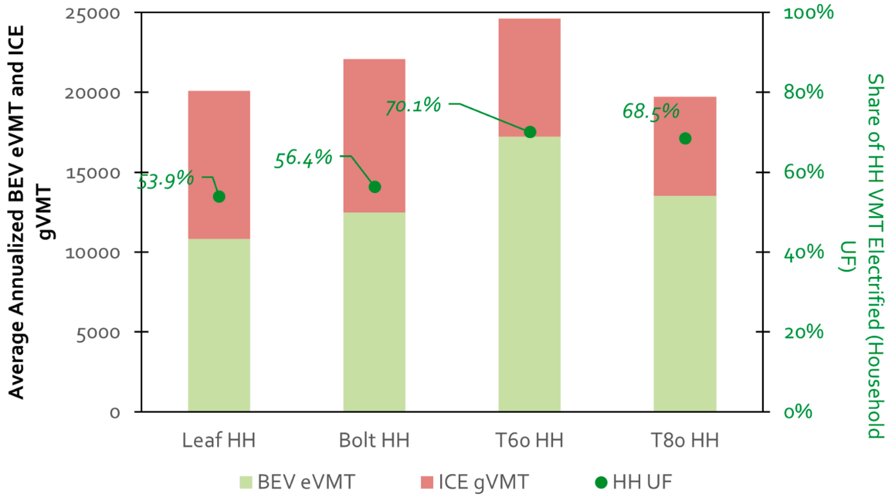
3.2. Observed utility factors and GHG profiles

Fig. 4 captures the association between average annualized mileage, UF, and GHG in the baseline scenario. Average annual eVMT of BEVs in our dataset is 13,000 miles–depending on the U.S. city, about 5–25% more than the average annual eVMT (9500–12,000 miles) in related studies (Khan and Kockelman, 2012, Tamor, 2019, Tamor and Milačić, 2015); and roughly 20% more than the annual mileage (10,500–11,000 miles) in national or statewide assessments reported for benchmarking (CARB, 2017a, ANL, 2015, Davis, 2019, Borlaug et al., 2020b). In 53 households, BEV drove longer than the ICE–15 Leaf, 17 Bolt, 11 T60, and 10 T80 households.

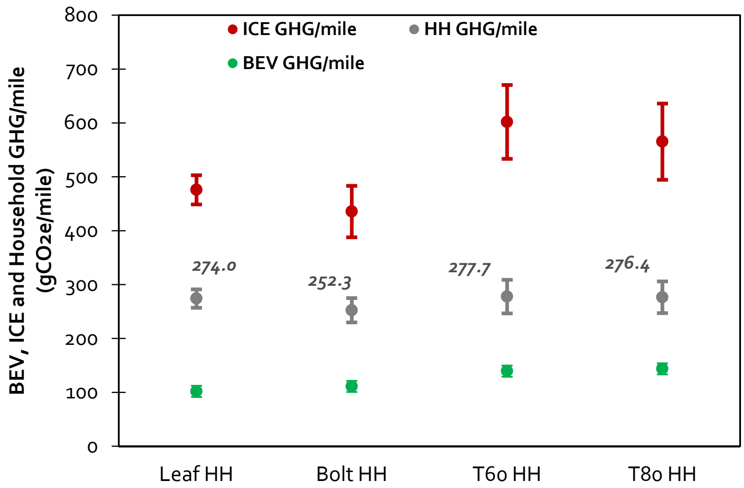
Average annual HH VMT, BEV eVMT, and UF increased with range, except in T80 households, and the resulting marginal UF gains do not always translate into marginal GHG benefits. Bolt households have the lowest GHG per mile and their UF is only slightly more than that of the Leaf HH UF, despite the Bolts having more usable range than Leaf. One reason could be because average ICE fuel economy is highest in Bolt HH (26.2 mpg), 10% more efficient than ICEs in Leaf HH, and 30–40% more efficient than ICEs in Tesla HHs. 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. Tesla HH (T60 and T80) ICEs are inefficient on average 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 whether the BEV only or the entire household is observed.

Daily charging frequency of Leaf and Bolt HHs is nearly same (0.8) but their DCFC usage is markedly different (Table 1). Leaf HHs have the highest share of DCFC sessions (17%), which might be due to the two years complimentary public charging offered by EVGo network to Leafs (EVGo, 2020). Share of DCFC sessions is lowest among the Bolt HHs (3%). Inability to fast charge or fast charging offered only as an add-on (GM, 2017) and lower number of Combined Charging System(CCS) plugs (2064) compared to the Tesla Supercharger network(2953 plugs) may be potential reasons (U.S. DOE, 2021). Roughly 10% of Tesla HH (T60 and T80) charging are DCFC sessions. Bolt HH eVMT and VMT is higher than that of Leaf HH but lower than that of T60 HH. The nature of ICE gVMT substituted and BEV usage by daily driving distances and speed intervals, and fuel economy of the ICE influence UF and GHG. These instances suggest that caution must be exercised when attributing correlation or causation of DCFC usage with travel demand allocation, UF and GHG profiles.

The subject of whether DCFC supplements regular home charging and enables more travel or substitutes routine charging is not part of this study. It must be remarked that motivations for fast charging could also differ. Some users might prefer parking and



(a)



(b)

Fig. 4. Average annualized eVMT, gVMT, UF, and GHG observed in the baseline reference scenario. (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.

charging over fast charging (Wolbertus and Van den Hoed, 2019), place a higher value on DCFC for intercity travel compared to intraregional travel (Greene et al., 2020), or accomplish nearly two-thirds of DCFC within 25-miles from home (Tal et al., 2020a).

3.3. *Absolute, type, and frequency of ICE gVMT replaced*

Revealed household travel demand allocation by driving distances and styles (Fig. 2) affects the opportunities available for additional BEV usage. The nature of ICE travel that could possibly be substituted by the BEV and its variations across different scenarios and BEV types is first presented. A reasonable basis for handling this inquiry is depicted in Fig. 5.

Scenario analysis showed that it is feasible to substitute 1500–3400 ICE gVMT over 85–97 days/year by adopting the travel day vehicle selection strategy alone (*S1*). In Leaf and Tesla (T60 and T80) households, this is realized by driving the BEV on 45% of days (ICE at home) and the remaining 55% of time driving the BEV for larger of the two distances. In Bolt HH, these splits were 30% and 70% respectively. Bolt HH's eVMT (3400 miles/year) increased the most in the *S1* scenario, followed by the T60 and T80 HH (roughly 2500 miles/year), and lowest in the Leaf HH (1400 miles/year). Nearly half of ICE travel replaced by Leaf and Bolts were of highway driving style (60mph +). In contrast, roughly half of ICE gVMT replaced in T60 households were of city driving style (45mph or less), which further increases to 70% in T80 HH.

By fully charging the BEVs overnight *and* selecting the BEV over ICE (*S2*), 2000–4000 ICE gVMT can be replaced. Compared to *S1*, this represents a 5–10% increase in days/year (90–108 days/year) and a 10–30% improvement in absolute ICE gVMT replaced.

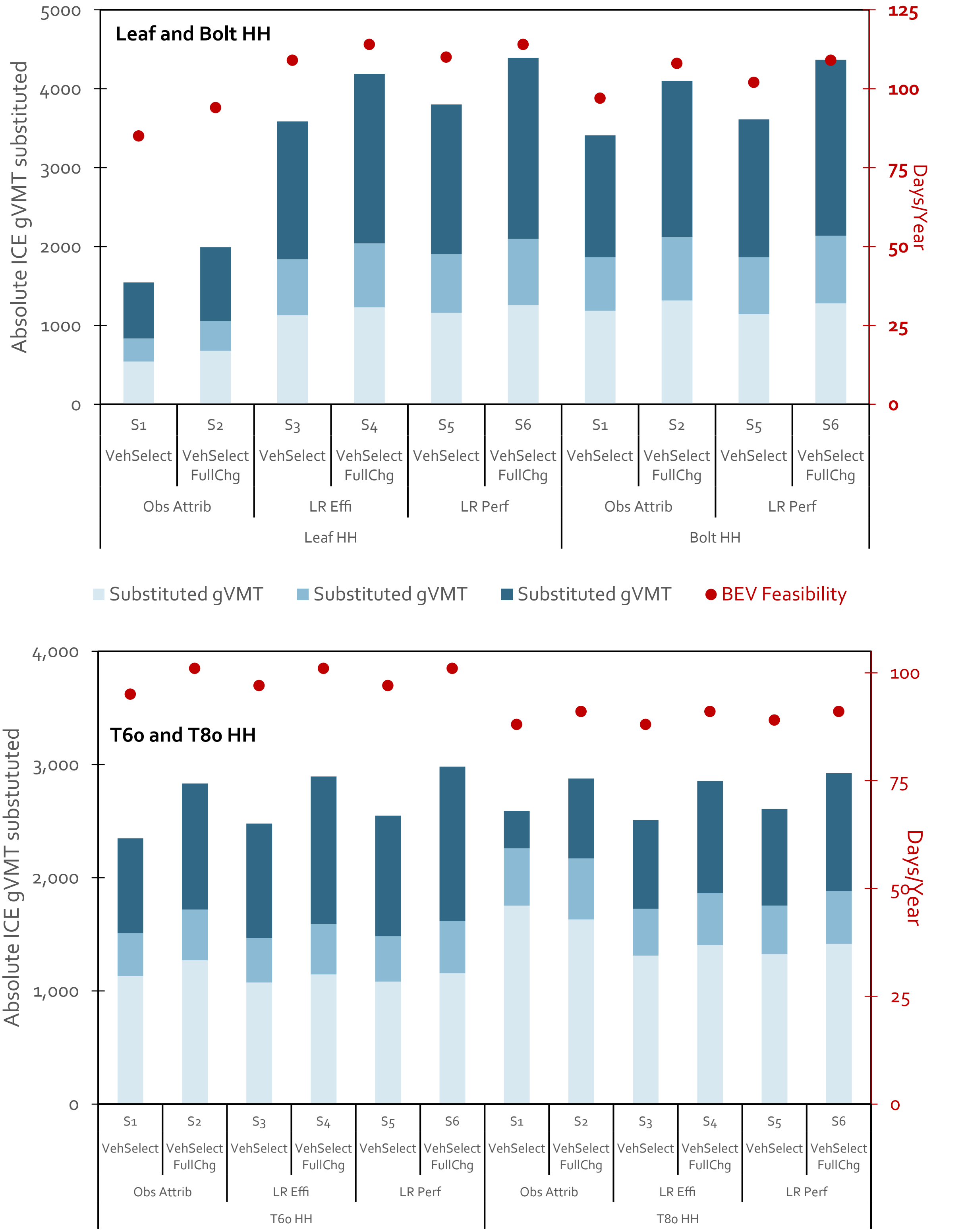


Fig. 5. ICE gVMT substituted by driving style(primary Y-axis) and BEV feasibility in days/year/household (secondary Y axis) in different scenarios.

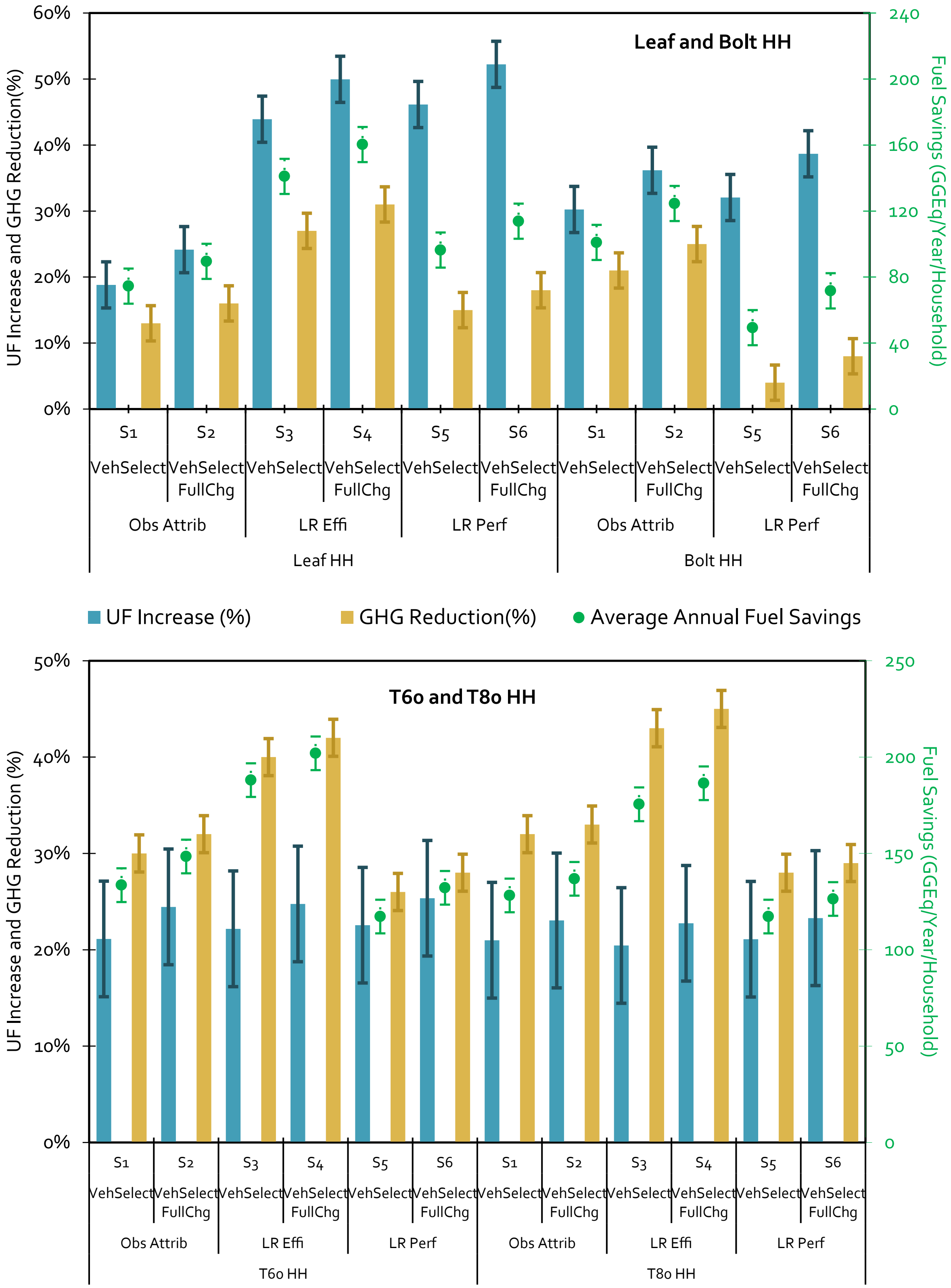


Fig. 6. Percentage change in household UF and GHG (primary Y-axis) and average annual fuel savings in GGEq (secondary Y-axis) relative to baseline *Obs_Beh* in different scenarios.

Disproportionately larger gains in ICE miles substituted in the *S2* scenario shows the value of fully charging overnight at home, besides just travel day vehicle selection as in *S1*. Range limited Leaf HH stands to benefit the most by upgrading to *LREffi or LRPerf* as they can substitute more than twice as much ICE gVMT as their current Leaf. Tesla HHs (T60 and T80) saw slight to negligible improvement in the substitution potential by upgrading to a *LREffi or LRPerf* (*S3 and S5*). When combined with fully charging overnight at home (*S4 and S6)*, relatively longer ICE travel on fewer days (120 miles; 2–7 days/year) could be substituted. The impact of different GHG abatement strategies on UF, GHG, and fuel savings considered in the scenario analysis are discussed in the next subsection.

3.4. Overall impact on household utility factors, GHG, and fuel savings

Scenario specific impacts on key performance metrics across different BEV types relative to their baseline observed values (Fig. 4) are depicted in Fig. 6. Compared to observed behavior, household UF increased on average by 20% in 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, an additional improvement of 2–6% in HH UF over baseline is possible. In *S2*, average UF was 0.64 in Leaf HH, 0.75 in Bolt HH, and nearly same in T60 (0.82) and T80 HHs (0.83). Compared to observed behavior baseline scenario, the combined effect of travel day vehicle selection and fully charging overnight at home (*S2*) reduces HH GHG by 25% and saves 125 GGEq in Bolt HH. Correspondingly, Tesla (T60 and T80) HH GHG reduces by 30% and saves 140 GGEq. On average, 12–16% of Leaf HH GHG can be reduced relative to baseline by travel day vehicle selection (*S1*) and full overnight home charging (*S2*), resulting in fuel savings between 75 and 90 GGEq.

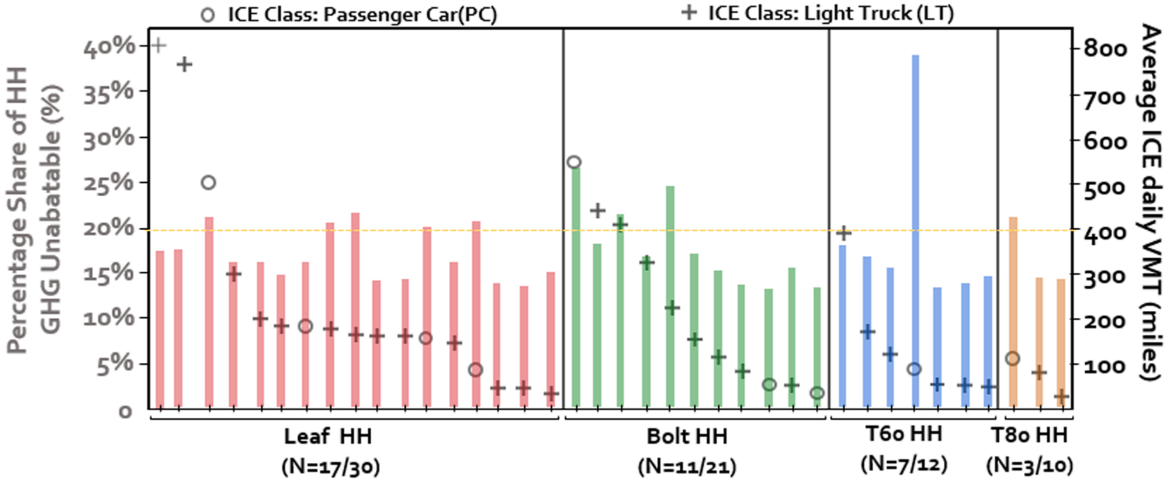
Upgrading the BEV causes a diverse set of outcomes that may compliment or even compete with one another. Beneficial impacts of longer-range on Leaf HH UF is clear. In the baseline scenario, average UF of Leaf HH is 0.54, and it increases to 0.64 if they fully charge overnight at home and use their existing Leaf (*S2)* instead of the ICE whenever feasible. This further improves to 0.72 by upgrading to *LREffi or LRPerf* (*S3, S5)* and 0.75 if combined with full overnight home charging (*S4, S6)*. These represent a 45–50% increase in Leaf HH UF from baseline. However, the ensuing GHG reduction and annual fuel savings noticeably varied depending on whether existing Leaf was upgraded to *LREffi or LRPerf*. Upgrading to a *LREffi* reduces HH GHG by up to 25–30% and save 140–160 GGEq compared to baseline. These GHG reductions and fuel savings are twice as much achievable with their existing Leaf. Fuel savings in Leaf HH reduces by nearly 30% from 140 to 160 GGEq if upgraded to *LREffi (S3,S4)* to 96–114 GGEq/year if upgraded to a *LRPerf (S5,S6).* The 15–18% HH GHG reduction in upgrading to a *LRPerf*, does not differ from what a Leaf HH can currently achieve by fully charging overnight at home and driving their Leaf (13–16%).

This is due to gains in UF enabled by *LRPerf* coming at the expense of lower driving electrical energy efficiency. Referring to Fig. 5, upgrading the Leaf to *LRPerf* substitutes relatively longer distances (35–40 miles) and highway driving style dominated ICE gVMT (52%). Typical ICE gVMT otherwise substituted by Leaf were shorter (18–21 miles) and slightly less highway driving style (48%). Moreover, *LRPerf* consumes 50% more driving electrical energy (0.384 vs. 0.248 kWh/mile) than a Leaf. Analogous explanation follows to highlight longer-range enabled UF gains can be counteracted by technology (kWh/mile, fuel economy) and user preference related (VMT allocation by driving styles and speeds between ICE and BEV) energy efficiency losses. The composite effect being diminishing GHG reduction and fuel savings. Conversely, technology and user preference related energy efficiency gains can further augment GHG reduction and fuel savings but at the expense of lower UF due to range limitations like a Leaf or range under-utilization in Bolts.

In Bolt HHs, upgrading to *LRPerf* improves UF by 30–35% in *S5 and S6* from 0.56 with negligible GHG reductions (4–8%) from observed behavior baseline scenario. These are considerably lower than what they could achieve without upgrading their BEV but by only driving them instead of the ICE (20% GHG reduction and 101 GGEq savings in *S1* over baseline) or combined with fully charging overnight at home (25% GHG reduction and 125 GGEq fuel savings in *S2* over baseline). Bolt HHs effectively 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 baseline).

Tesla HHs (T60 and T80) displayed relatively consistent 20–25% improvement in UF and 30% GHG reduction from baseline irrespective of whether they kept their current T60/T80 *(S1, S2)* or upgraded to a *LRPerf* BEV *(S5, S6)*. The UF gains when upgraded to *LREffi* BEV *(S3, S4)* were comparable to baseline improvements realized using their existing T60/T80 or *LRPerf* BEV. However, there were noticeable differences in the resulting GHG reduction and GGEq savings. Household GHG reduced by 40–45% from baseline when Tesla HHs (T60 and T80) upgrade to a *LREffi* BEV. This corresponds to additional 10–15% GHG mitigation and 50 GGEq fuel savings over their current T60/T80 *(S1,S2)* and upgraded *LRPerf* BEV *(S5,S6)* scenarios. Referring to Fig. 2, observed driving behavior of Teslas reveal their preferences for highway driving style and longer daily distances. Roughly 35–40% of Tesla eVMT were at highway driving style (60 mph +) and daily distances 100 miles or more accounted for nearly 30% of their annual eVMT. These preferences are clearly distinguishable from the Leaf and Bolt HHs, where the ICE is preferred for such travel needs. When Tesla households upgrade to a *LREffi*, their GHG reduction benefits are intensified due to the convergence of the following factors. First, the intrinsic technology related energy efficiency improvement of 30% in *LREffi BEV* over a Tesla (0.247 kWh/mile vs. 0.35 kWh/mile). Second, nearly 50% of Teslas substitution patterns are 45-mph or less city driving style ICE gVMT (Fig. 5). This is perhaps reflective of Tesla households observed travel demand allocation by speeds, distances, and vehicles (Fig. 2).

Thus far, substitution potential of BEVs, UF, GHG, and GGEq savings cross-BEV and intra-scenario comparative assessments were described. Modalities of interactions between observed usage, potential for additional BEV usage, and its consequential effect on chosen metrics were discussed. Empirical analyses and inferences on potential trade-offs or diminishing returns were exemplified from a theoretically attainable perspective, albeit reliant on varied assumptions and scenario settings. In the proceeding subsection, what's left out is narrowed down, i.e., usage patterns and their associated GHG that scenario analysis couldn't mitigate.



	Hard to abate GHG Days/year/household				
Number of HH	*Total*	*Average*	*Min-Max*	*Average ICE gVMT*	*Average share of Hard to abate GHG*
Leaf: 17 HH	85	5	2-18	302	12%
Bolt: 11 HH	61	5.5	2-13	312	11%
T60: 7 HH	23	3.3	2-8	293	7%
T80: 3 HH	6	2	1-3	333	4%
Overall: 38 HH	***175***	***4.6***	***1-18***	***306***	***10%***

Fig. 7. Characteristics of hard to abate GHG days attributable to the sub-sample of 38 households. Contribution to total HH GHG (left Y-axis) ranked in descending order using markers for ICE class (PC or LT) inset. Each vertical bar denotes a household and average ICE VMT displayed on right Y-axis.

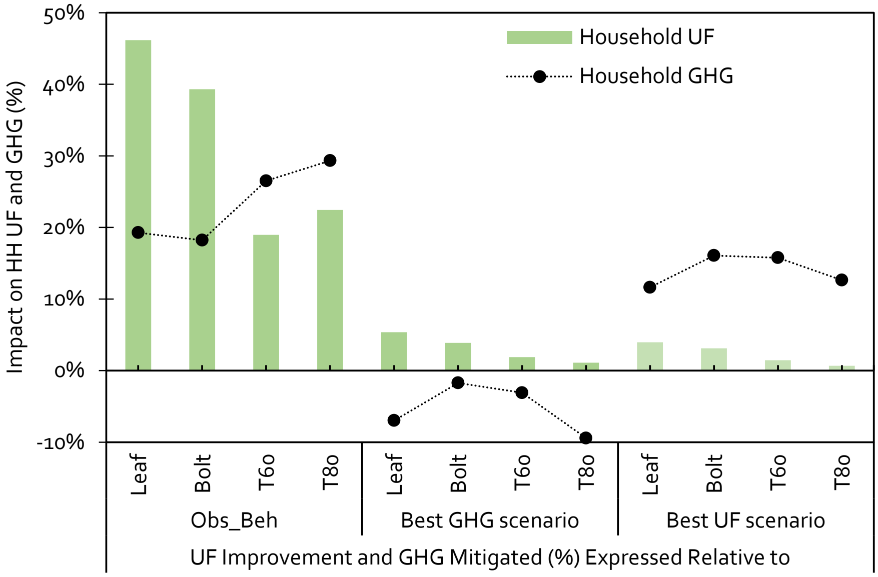
3.5. Deeper GHG reductions and future BEV attributes

Range decisively influences purchase decisions, driving and charging behavior, and the dynamics governing household travel demand allocation. Due to the subjective nature of usage preferences, perception and valuation, BEV acceptance is typically understood through indicators like *threshold of inconvenience, days requiring adaptation(DRA),* and its sensitivity to travel patterns and charging options (Khan and Kockelman, 2012, Wenig et al., 2019, Pearre et al., 2011). We build upon the notion of range acceptance and examine range prospects from UF and GHG operationalized in the travel behavior of households analyzed in this study. The impact of a state-of-the-art BEV on UF and GHG is contrasted with the scenario results. The purpose is to gain a better understanding of the practicalities of range anxiety, sufficiency, and actual necessity.

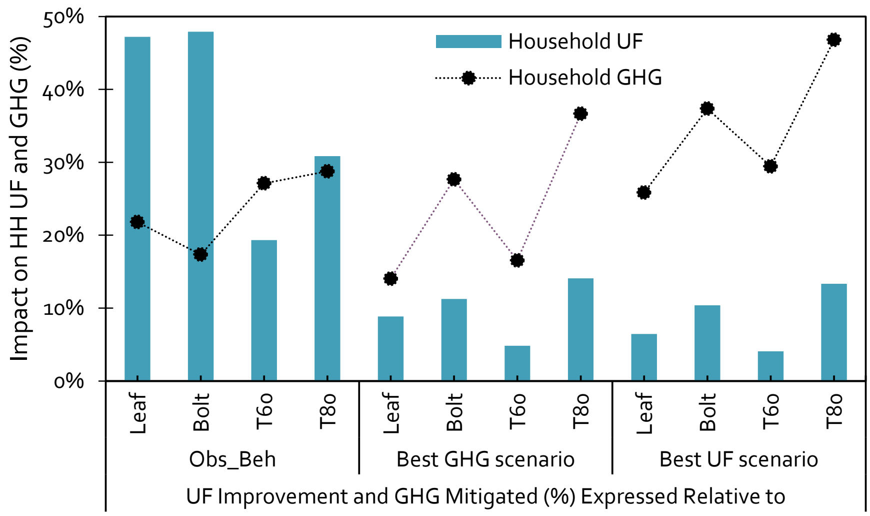
Currently available BEV with longest range, 400-mile Tesla Model S (Tesla, 2020) was chosen. A reasonable use case for a 400-mile BEV can be determined from the observed travel data. Of particular interest are the subset of days when ICE gVMT exceeds even the upgraded BEV attribute range in *S6* (275 miles, Appendix Table A3). Appendix Fig. A5 depicts the average number of days/year BEV cannot replace the ICE under different scenarios, and the corresponding number of households. Potential for further GHG mitigation resulting from 400-mile BEV instead of the existing BEV is investigated on these travel days with hard to abate GHG.

The characteristics of these travel days observed are shown in Fig. 7. Source of hard to abate GHG is attributable to 175 days of travel in 38 HHs (17 Leaf, 11 Bolt, 7 T60, and 3 T80 HHs). These travel days averaged 10% of total HH GHG (4–12% by BEV type). On these days, ICE drove on average 306 miles and twenty-nine of these households used their larger footprint (LT segment) ICE.

Observed behavior and scenario specific outcomes on UF and GHG discussed were based on *ex-post* availability of BEV make, model, and specifications. To ascertain the UF and GHG prospects of advanced BEV models, two options to assign this 400-mile BEV range scenario were considered–all 73 HHs or only the sub-sample of 38 HHs upgrade to a 400-mile BEV. The UF and GHG due to the 400-mile BEV were compared with the corresponding best case among the six scenarios already analyzed. Relative to observed behavior baseline scenario(*Obs_Beh)*, UF and GHG improves by 20–50% and 20–30% respectively, Fig. 8(a). Without upgrading to 400-mile BEV, comparable (in T60 and T80 HHs) and roughly half (in Leaf and Bolt HHs) of these benefits can be achieved by fully charging their existing BEV overnight at home and driving them instead of the ICE whenever feasible (Fig. 6). Their impact relative to the best UF and best GHG scenario is comparatively smaller and may 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.



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



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

Fig. 8. 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.

Within the sub-sample of 38 HHs that solely contributed to the hard to abate GHG, 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, T60, and Leaf HH stand to gain the least, Fig. 8(b). Out of the 175 days, 400-mile range BEV substituted ICE miles on 120 days, nearly halving (5%) the proportion of hard to abate GHG (10%). The remaining 55 days (20 Leaf, 26 Bolt, 6 T60 and 2 T80 travel days) counted for 5% of hard to abate GHG. Stylized and simplified approach based on a small sample of households notwithstanding, these are just a few examples that illustrate that longer-range though could alleviate inconvenience, doesn't always translate to corresponding GHG and UF gains, and might create unintended consequences when misaligned with household travel demand.

4. Discussion

This study explored the electrification and emission reduction benefits of BEVs in 2-car households using multi-year observational travel data from seventy-three California households (30 Nissan Leaf, 21 Chevrolet Bolt, 22 Tesla Model S). The potential for increasing their utilization and GHG abatement benefits was evaluated using scenario analysis. These scenarios represent specific and combined effects of travel day vehicle selection, full overnight home charging, and BEV attribute upgrade (range and efficiency or sportier performance). Comparative assessments with revealed usage, across BEV types, and within scenarios were performed through different metrics.

Driving the BEV instead of the ICE whenever feasible is the simplest strategy that a household can take. This alone can cause 10–20% GHG reduction while electrifying 20–30% more miles compared to baseline. Though these are under ideal conditions, there could be any number practical reasons for choosing to do otherwise–number of persons traveling, space and comfort, destination charging access, and range anxiety concerns. Additional benefits (GHG reduction and UF increase from baseline) from fully charging overnight are more noticeable in Leaf and Bolt HH compared to Tesla HHs. Despite Bolts having more than twice the range of Leaf, Leaf and Bolt HHs allocate relatively similar ICE and BEV miles by driving distances and styles. In Tesla (T60 and T80) HHs, the BEV was dominantly used for longer driving distances at highway driving style speeds (60mph +) compared to Leaf and Bolt HHs. Such preferences could correlate with the technological attributes and specifications of a Tesla, or because of self-selection by such households. These instances observed in this study clearly deviate from a conventional line of reasoning that BEVs are fit for or substitute short-distance travel. Range alone cannot objectively indicate their real-world usage preferences, let alone their substitution potential and GHG reduction benefits. Simply put, when the quantity of miles substituted by the BEV increases, UF improves whereas GHG abatement depends on both quantity and quality of ICE miles substituted and the driving electrical energy efficiency of BEV. For example, a 15% increase in UF of T60 HH comes at the expense of a 10% increase in GHG compared with Bolt HH in the observed baseline.

Outcomes of scenario analysis indicated an array of consequences depending on the metric and BEV type. This is because of differential attribute substitution patterns and powertrain efficiencies. Their combined effect could be additive or counteracting. By upgrading to a longer-range efficiency-oriented BEV, a Leaf HH benefits from more than a twofold increase in range, while driving electrical energy efficiency remains the same. Roughly half of ICE gVMT it substituted were of relatively fuel inefficient city driving style. The net effect being a 30% reduction in HH GHG and a 50% increase in UF compared to the observed baseline. When a Leaf HH upgrades to a longer-range performance-oriented BEV, owing to a reduction in driving electrical energy efficiency, almost 15% of GHG gains achievable with a longer-range efficiency BEV is offset. Approximately half of fuel inefficient highway driving style ICE gVMT is still substituted without altering the relative UF improvement over observed baseline.

Understanding daily driving needs and how various market segments perceive and value BEV attributes is crucial for auto manufacturers. This would aide in optimizing BEV design specifications and model offerings. Real-world ramifications of future BEVs are vulnerable to the subjective and diversified user needs, and how it matches with the BEV attributes. Analysis showed that the impact of a state-of-art 400-mile BEV upgrade across all 73- households has no tangible UF benefits and could negatively impact GHG compared to best case GHG and UF from among the six scenarios. Even among the sub sample of HHs solely attributable to hard to abate GHG, it assists them only on 2–5 days/year.

Interplay between vehicle attributes and household preferences shapes the contours of BEV utilization. Household preferences manifest at different temporal scales–trip level driving styles; charging duration and frequency; daily household VMT and appropriation; time to adapt to BEV attributes; and long-term purchase decisions. Depending on the policy goal and metric, nature of these interactions alongside the set of abatement strategies leads to diverse conclusions. This is partly due to the sensitivity of results and its exposition to the ambit of scenarios. Scenario selection criteria and assumptions focused mainly on increasing UF or maximizing BEV usage. It is necessary to note that the same scenario analysis framework could cause different utility factors and substitution potential if the goal is to minimize total household GHG or TCO for example. Typical and atypical travel needs vary, and the travel day usage preferences are heterogeneous across different households and BEV types. This would influence the household's attitude, assessment, and acceptance of range, besides their individual operational and TCO criteria. Study emphasized on the *here and now* and prospective WtW GHG and UF implications of BEVs in multi-car households. Average annual fuel savings were included in our comparative valuation to avoid conflating or confounding GHG implications with private TCO gains.

While a total life cycle costing approach was omitted due to study scope, data collected, and survey design, certain aspects are noteworthy. The ratio of ICE to BEV driving costs in the U.S. varies between 1.4 and 3.6 and the tipping point fuel economy favoring ICE usage over BEVs is estimated to be 57.6 mpg (Sivak and Schoettle, 2018). Tipping point fuel economy would have to be even higher because gasoline costs 40% more in California ($3.502/gallon) compared to national average of $2.575/gallon (AAA, 2021) and fuel economy of ICEs analyzed in this study (23.3 mpg) is appreciably lower than the tipping point fuel economy. It is challenging to identify with precision why ICE was chosen over the BEV or vice versa and the eVMT/gVMT using only logger data. Even if logger data is integrated with driver information, activity or purpose, and locational characteristics , it is complicated to capture the entire spectrum of preferences. A controlled pre/post BEV inclusion study might track vehicle choice and travel demand allocation tendencies in multi-car households (Jensen and Mabit, 2017).

Trade-offs between range, UF, and GHG are exemplified in the breakdown of WtW household GHG by vehicle (Fig. 4) and in the 400-mile future BEV scenario (Fig. 8). In certain cases (e.g., Teslas in observed baseline and all 73 households upgrading to a 400-mile BEV), longer-range could negatively impact GHG but improve UF. This broadly concurs with related studies that suggest increasing the range might also negatively affect private TCO metrics (Karlsson, 2020) and DCFC network expansion costs (Tamor, 2019, Wenig et al., 2019). Though not part of this study, descriptive analyses presented can assist in parametric updates, calibration and verification attempts to strengthen the representativeness or correct for the lack thereof in vehicle choice modeling (Stephens et al., 2017), powertrain simulation tools (Brady and O'Mahony, 2016), integrated assessment models (Yang et al., 2015), and annual mileages in LCA studies (Elgowainy et al., 2018).

Applicability of this study has major implications for policy makers, vehicle OEMs, and prospective BEV users.

4.1. Regulatory assessments and policy domain

- *Reducing the "performance gap" between test cycles and real world:* Standardized testing practices are carried out in a highly controlled environment that is often more conservative than real-world driving conditions. Improving the accuracy of energy consumption measurements and properly communicating BEV range mirroring their real-world driving patterns is essential. If range and energy consumption were strictly seen as a function of vehicle specifications, one could even present a case for uniformity in their evaluations and testing (EC, 2014). Development of BEV specific naturalistic driving cycles to ascertain their feasibility (Faria et al., 2019) and transition to Worldwide Harmonized Light Vehicles Test Procedure) are pertinent examples.
- *Eco-driving and in-use performance monitoring:* Widespread penetration of Information and Communication Technology(ICT) devices and advancements in Internet of Things(IoT) has facilitated real-time data collection of BEV's driving behavior, ambient conditions, and road traffic. Range and energy consumption can be estimated dynamically. This can be given as a feedback to encourage eco-driving behavior and increase available range (Günther et al., 2020). Vehicle telematics and remote monitoring have been used for OBD-II compliance enforcement (Posada and German, 2016), reporting driving and charging electricity use for GHG accounting, and utility rebate programs for smart metering (CARB, 2019b, CARB, 2016).
- *Incentive design:* Positive association between BEV uptake and financial incentives like subsidies, fee waivers, and tax credits is well established (Jenn et al., 2018, Wang et al., 2019). Differing views on the economic viability and distributional implications of these incentives that were voiced in the past (Holland et al., 2019, Sovacool et al., 2019) could once again resurface. Restricting eligibility of high end BEVs like Tesla (Hardman et al., 2017), effectiveness of flat rate subsidy design, lack of differentiation between low and high annual eVMT (T60 vs. Leaf, Table 2), and factoring income, range, and ownership type (Yang et al., 2016), Victorian State Government's road user fee for BEVs (Vicroads, 2020), and availing either purchase subsidy or carpool lane stickers in California (CVC, 2019) are prime examples. In the future, OBD-II regulations and in-use monitoring can be leveraged to tie incentives to actual electric miles traveled and electrical energy charged.
- *Charging infrastructure adequacy:* Private home charging will be the most preferred charging location due to low cost of charging and convenience. Support for home charging through financial incentives and preferential time-of-use rates (Lee et al., 2020, Wood et al., 2017) should continue. To sustain BEV uptake and increase utilization, reliable access to public charging network is vital. Coverage, density, and capacity of public charging infrastructure is determined by range and accessibility to private home or workplace charging. Public fast charging infrastructure is also influenced by–BEV ranges available and related private TCO decisions (Nykvist et al., 2019);economics of installation and utilization rates (Burnham et al., 2017, Gnann et al., 2018, Funke et al., 2019b);charging power; and grid impacts (Wolbertus et al., 2020, Jenn et al., 2020).
- *Electricity generation mix:* California's total electricity generation is dominated by natural gas (35%) followed by renewables (30%), and only 3% of electricity is generated by coal power plants (CEC, 2019). Nationwide, coal power plants and renewables account for 25% and 15% of electricity generated respectively (EIA, 2019). The relative GHG benefits of BEVs would be higher in regions that are more fossil-fuel oriented. Grid decarbonization by shifting from fossil fueled to renewables combined with incentives to shift charging overnight would further reduce BEV charging emissions (McLaren et al., 2016).
- *Life-cycle Assessment:* Social and supply chain risk concerns associated with mining of rare earth elements has urged the need for a life cycle or circular economy approach in BEV environmental impact assessments (EEA, 2018, Lattanzio and Clark, 2020). Though this issue deserves serious scrutiny, inclusion of vehicle cycle GHG in LDV efficiency standards and or BEV policies is difficult. Sensitivity to life cycle inventory and system boundary, knowledge gaps, data uncertainty and quality issues because of the supranational scale of operations, and imposing liabilities on OEMs due to activities outside their purview, are reasonable grounds for excluding vehicle and battery manufacturing emissions (Hall and Lutsey, 2018, T&E, 2020). Suffices to say, grid decarbonization, battery secondary life and recycling are vital to reduce battery manufacturing and end use GHG.

4.2. Future household and OEM portfolio

Future buyer intentions and household vehicle attributes:

Range, cost, and charging access barriers have confined a major share of BEVs to the early adopter segment. Fraction of California's population with early adopter characteristics is only 4% and this segment is expected to saturate by 2030 (Lee et al., 2019). This raises the following question: How would the purchase motivation of early mainstream adopters differ from early adopters? The breadth of market diffusion and BEV purchase motivation studies have been expanded to cover potential early or late mainstream adopters (Axsen et al., 2016). These are mostly determined based on sociodemographic and psychographic segmentation by vehicle attribute valuation over comparable alternatives. Despite the wide spectrum of possibilities, certain trends stand out–potential early mainstream adopters preferring PHEV (Wolinetz and Axsen, 2017); mainstream household that value economic utility over environmental benefits prefer PHEVs (Lane et al., 2018); larger footprint vehicles are prime submarket for PHEVs (Higgins et al., 2017); discontinuance among short-range lower end BEVs due to long recharge times and today's longer-range high-end BEV user might purchase another BEV (Hardman et al., 2016); potential passenger car segment BEV buyer is less concerned about ownership costs or on-road performance (Mohamed et al., 2018). These aspects allude to the emergence of subpopulations beyond the early adopters with a clear inclination towards the type of PEV(BEV/PHEV or both) and desirable attributes like size, range, performance, comfort, and fuel economy.

Vehicle OEM trends, policy signals, and model diversification:

Automakers need to fulfill twin purposes of ensuring their vehicle offerings cover the diverse needs of prospective BEV/PHEV buyers, whilst meeting fuel economy, GHG standards, and ZEV mandate, as needed. They must harmonize policy signals, supply risks, and demand side requirements. Any misalignment between vehicle specifications (e.g., range) and user preferences could over or under-estimate market barriers. To hedge against heterogeneous user preferences, range diversification is essential. Uncertainties in battery technology advancements and cost reduction trends jointly influence required charging infrastructure. Policy goals and design have a cascading effect on costs, support, risks, and effectiveness. For example, a push towards long-range 400-mile BEV pathway without achieving required battery cost reductions or investments in charging infrastructure, could worsen barriers to entry as prospective BEV/PHEV buyers would not favorably view the attributes and specifications.

It must be underscored that a household's future vehicle purchase decisions are not independent of existing vehicle's attributes. It is quite possible that external improvements to an existing or first vehicle's attribute (e.g., longer range , fuel economy) might be negated if the household purchases a gas guzzler as their next car. This is widely acknowledged in attribute based fuel economy standards (Archsmith et al., 2017) and applies to the case of BEV households as well. For sustained GHG reduction, electrification of the *other car* is vital. In the U.S., sales of larger footprint SUVs, crossover, minivans, and pickup trucks have outpaced that of passenger cars (Schoettle and Sivak, 2017, Davis and Boundy, 2020). It is more likely that majority of *other cars* are larger footprint vehicles. Automakers should target this niche market by continuing to expand their portfolio of Plug-in hybrid SUVs, minivans, and crossovers. The correspondence between model offerings and the developing PEV sub-markets beyond early adopters would have major consequences on fuel economy and GHG standards compliance pathways (Laberteaux and Hamza, 2018, Sen et al., 2017). It is reasonable to expect that the next phase of GHG assessments and electrification benefits to focus on BEV-PHEV 2-car households. For example, a 100-mile Nissan Leaf BEV and 35/50-mile longer-range PHEV like Volt or Chrysler Pacifica Crossover PHEV. Electrification benefits and GHG profile of such households would be examined in our future work.

4.3. Limitations and further research

Generalizability is restricted by the small sample size of niche early adopter BEV users belonging to 2-car California households in a major market supported by a favorable policy environment. Sample size limitations and selection bias are unavoidable in observational travel behavior studies. Households included in this study are not a statistically accurate representation of the California population. Instead, they reflect early adopter socio-demographics, purchase motivations towards top selling BEV models, intra-household preferences, and usage patterns. Monitoring BEV driving and charging behavior for a year alongside the *other car* gives sufficient time for users to familiarize with BEV attributes and captures a wide spectrum of household travel needs.

Simplifying assumptions embedded in the scenario analysis framework, though justifiable, may not capture all factors that influence a households' immediate to long-term decisions. Results presented are aimed to be *illustrative* subject to caveats and limitations, rather than *definitive* with the benefit of perfect oversight. As BEV market matures and adoption rate in multi-unit dwellings increase, reliable home charging access is not a guarantee. Fortunately, an increasing number of demand side incentives and regulatory actions target these geodemographics to mitigate charging barriers in multi-family and apartment housing (Lopez-Behar et al., 2019, CALGreen, 2019). In multi-car households with 2 or more drivers, activity patterns and dwelling times of both vehicles might vary. Cost and non-cost barriers further constrain the feasibility set of trips, days, and miles where substitution is possible. Considering BEV substitution potential at daily timescales by relaxing the locational constraints from home is optimistic but concerns only 3% of time in this study. Prospective BEV household's long-term purchase decisions are motivated by TCO considerations. This is decoupled in this study to achieve a balance between scenario selection without diluting real-world performative aspects and revealed household preferences.

Despite these caveats, study provides valuable insights on the actual and potential benefits of BEVs at the household level, hitherto scarcely explored. Future work will investigate the environmental impact of PHEVs in two-car California households using observational data of similar nature presented in this study. The scenario framework will be expanded to include cross-vehicle (ICE to BEV or PHEV) and cross-technology (BEV to PHEV and vice versa) attribute substitutions to study the effect of electrifying both vehicles, especially the larger-footprint ICEs. Nature of policy interactions (complimentary, substitutable, or counteracting) between fuel economy standards and electrification policies will be explored. Role of public DCFC in supplementing and or substituting routine charging and its impact on travel distances would also be studied. Potential avenues for future exploration include–incorporating spatiotemporal aspects to refine charging behavior assumptions; discrete choice modeling of travel day vehicle selection and charging decision; and integrating a systems or life-cycle perspective on economic value proposition and environmental assessments.

5. Conclusions

Divergence of real-world BEV usage patterns from expectations poses problems for policy makers and automakers. Information about real-world BEV usage is valuable for policymakers, as it will offer insights on current barriers and opportunities to BEV utilization. It can also help make informed decisions on their future policies to encourage their usage and maximize their GHG benefits. Understanding daily driving needs and how different market segments perceive and value BEV attributes is crucial for automakers to ensure future BEV design and model offerings are aligned with user preferences and needs. It is essential to frame and appraise BEV usage and GHG benefits in a manner that reflects current and future landscape of consumer awareness, purchase decisions, and driving and charging preferences.

Studying BEV usage in isolation could lead to inaccurate estimates of their GHG benefits, since most BEVs belong to multi-car households. This highlights the importance of gauging their real-world environmental performance from a household perspective that considers usage patterns of the BEV and the *other car*. To improve our understanding of electrification and emission benefits of different BEVs, it is important to include preferences such as driving styles and distances allocated between ICE and BEV, 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.

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Notes

Data availability statement: The data that support the findings of this study are available from the Plug-in Hybrid and Electric Vehicle Center, Institute of Transportation Studies at University of California, Davis. The restrictions as per University of California, Davis Institutional Review Board Administration and the Institute of Transportation Studies, Davis, and the California Air Resources Board apply to the availability of these data.

CRediT authorship contribution statement

Seshadri Srinivasa Raghavan: Conceptualization, Methodology, Writing - original draft, Validation, Visualization, Writing - review & editing, Software. **Gil Tal:** Conceptualization, Methodology, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Sampling comparisons and select survey responses.
See Table A1, Fig. A1, Table A2
Observed range, fuel economy, and energy consumption
See Figs. A2–A5
See Table A1–A5

Table A1
Sampling comparisons between observed and California Clean Vehicle Rebate Project(CSE, 2020) (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	10,930	17,516	707	2039	8184
PGE	57,256	76,099	11,630	10,348	35,278
SCE	41,217	57,272	3113	5692	32,412
SDGE	14,409	19,543	1700	2039	10,670
SMUD	3359	4218	645	579	2135
Other	9288	12,657	1315	1690	6283
Number of BEV rebates issued	*136,459*	*187,305*	*19,110*	*22,387*	*94,962*
Percentage share of CVRP subset			***14%***	***16%***	***70%***
Percentage share of Total CVRP		***73%***	***10%***	***12%***	***51%***

PGE (40%) accounted for the largest share CVRP rebates issued to BEVs followed by SCE (30%), SDGE(10%), LADWP(8%) and SMUD(2%).
^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.

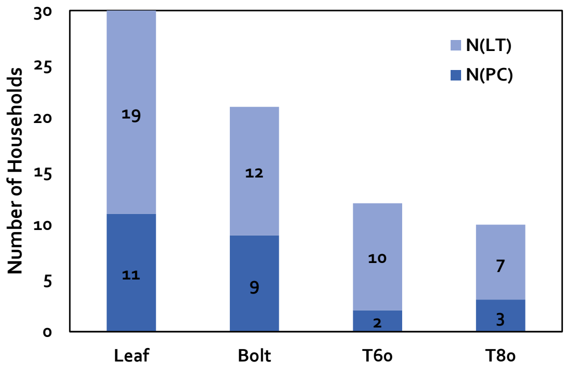


Fig. A1. Number of households by BEV type and ICE vehicle class: Passenger Car(PC) or Light Truck(LT) . Light Truck class includes station wagons, sports utility vehicles (SUV), vans, and pickup trucks.

Table A2
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(CAV) 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	–	–	–	

*These CAV decals potentially reduce commute time by 28% and save roughly $540 per vehicle in avoided tolls (Ji and Tal, 2019).

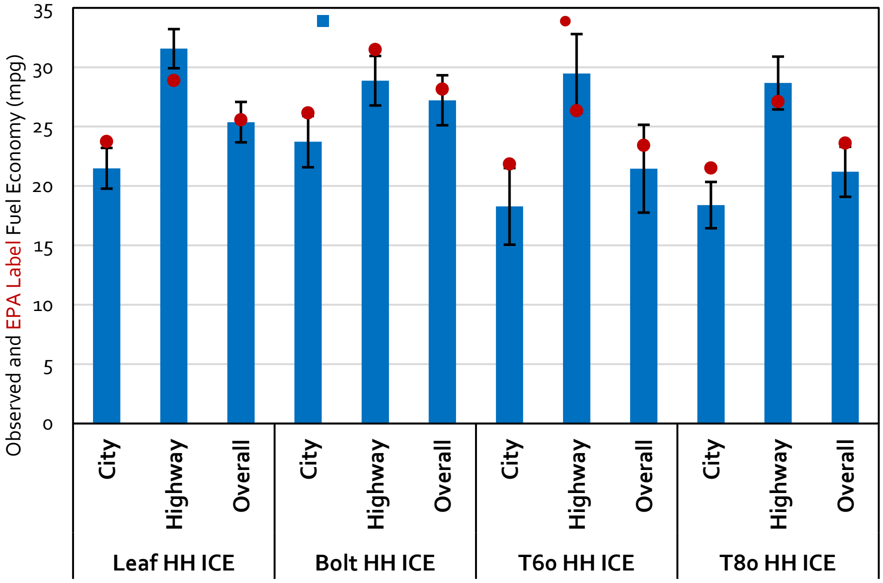


Fig. A2. Observed and EPA label fuel economy(U.S. EPA, 2020) (mpg) of the ICE by driving styles in different BEV households(HHs).

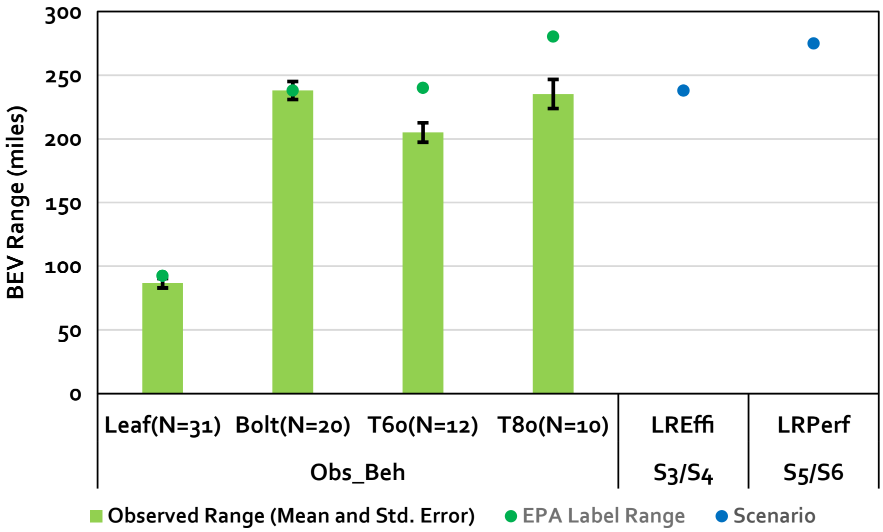
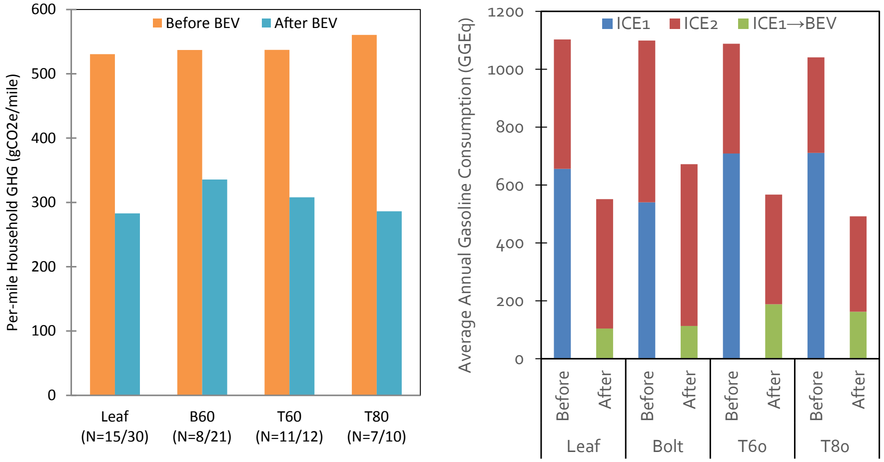


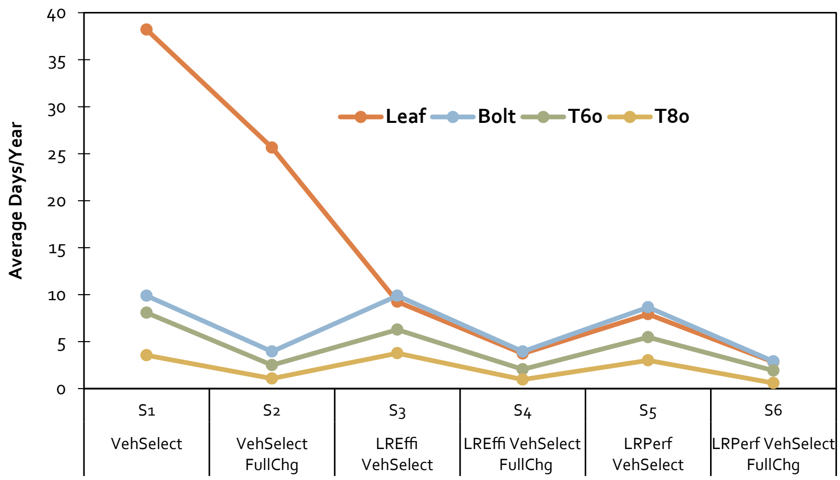
Fig. A3. Observed and EPA label range (miles) of the BEV by driving styles. Light green columns and the black bars depict the mean and standard error of observed range. Dark green dots are the EPA label average fuel economy. Blue dots show the upgraded BEV attributes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



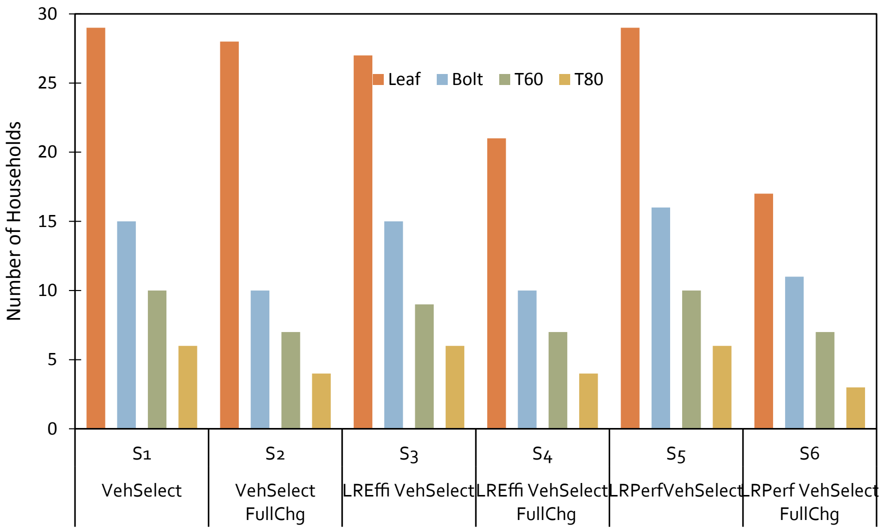
(a) Household GHG (gCO2e/mile) before/ after BEV purchase

(b) Average annual fuel consumption (GGEq) before/after BEV purchase

Fig. A4. Pre-post BEV purchase emissions and fuel consumption.



(a)Average days/year BEV cannot substitute the ICE



(a) Corresponding households contributing to BEV infeasibility

Fig. A5. (a) Number of households and (b) average days/year BEV cannot replace ICE across all scenarios and by BEV type.

Table A3
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

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.

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

[&] For scenarios *S3 VehSelect and S4 VehSelect 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 VehSelect and S6 VehSelect 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(U.S. EPA, 2020) database (vehicle id 42755) was used. To account for divergence from real-world energy consumption, we 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).

Table A4
Observed and laboratory testing estimates of Recharge Allocation Factors (AAA, 2019).

	Observed	Lab testing environment conditions					BEV Model
		75°F	20°F	95°F H	20°F	95°F	
			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	1.203	1.147	1.181	1.145	1.183	1.155	2017 Tesla Model S 75D
T80	1.150						

Table A5
Survey responses to BEV purchase decision.[1]

Type of Replacement	Leaf HH (N = 30)	Bolt HH (N = 21)	T60 HH (N = 12)	T80 HH (N = 10)	Total HH (N = 73)	Previous Car Details
Additional car	5	1	0	2	8	Missing
Replaced car sold/returned in 3 months prior to logging study	3	1	1	1	6	Missing
Sold/no longer have	0	9	0	0	9	Missing
Sold/no longer have	22	10	11	7	50	Available
Identical replacement	*7*	*0*	*0*	*0*	*0*	
Leaf to Bolt	*0*	*2*	*0*	*0*	*0*	
Valid Sub-sample of HH for pre-post BEV GHG assessment	*15*	*8*	*11*	*7*	*41*	

[1] Replaced vehicle (ICE1) energy and emissions were obtained by *matching* the model, year, and make reported in the survey with the EPA fuel economy database. Combined city/highway fuel economy values were used. Since the study does not control or focus on explicitly denoting main and second car based on annual VMT, we assumed that the ICE(ICE2) observed in this study and its VMT remains the same before/after BEV purchase.

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