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Electrification of vehicle miles travelled within the household context

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Summary

In this paper, we investigated Plug-in electric vehicles (PEVs) within the household context and analyzed how household factors impact utility factor (UF) and electric vehicle miles travelled. We used a dataset with one-year logger data on all actively used cars in 71 households owning a PEV in California. Our results indicate that for the whole household, a PHEV with a range of 36 miles can electrify almost the same share of miles as a BEV with 80 miles range. Furthermore, a higher frequency of long-distance trips lowers the UF of a PHEV and owning a conventional car with higher fuel economy lowers the UF of the household.

Keywords: PHEV, BEV, user behavior, utility

1 Introduction

The use of plug-in electric vehicles (PEVs), split into two main categories, battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), combined with the decarbonization of the electricity sector, can help reduce greenhouse gas emissions in the transport sector [1]–[4]. BEVs use an electric drive train for propulsion and their only source of energy is their rechargeable battery packs. PHEVs on the other hand combine an electric drive train with a conventional one, which leads to a more complex analysis of fuel economy compared to BEVs and internal combustion engine vehicles (ICEVs) [5].

Utility factor (UF) of a PHEV —defined as the share of electrified vehicle miles travelled (eVMT) within total vehicle miles travelled (VMT)— is the most common metric in analyzing the performance of PHEVs in order to understand to what degree they provide emission-free travel. There are two main approaches to assess the UF that are present in the literature. The first approach is to run simulations based on test-cycles or transportation surveys. In this approach, the UF is calculated under certain assumptions regarding the charging frequency, vehicle characteristics and driver characteristics [6]–[12]. Standardized methods that rely heavily on assumptions are criticized for not accounting for complex scenarios. SAE J2841, for instance, is based on the assumptions that each vehicle starts the day fully charged, does not charge until after the last trip of the day and only charges once a day; it also assumes that PHEVs are driven in the same patterns as national average vehicles [13], [14]. Bradley and Quinn [13] investigate how different assumptions in these standards would result in different UF calculations, and they find that UF calculations are very sensitive to assumptions regarding charging behavior, vehicle age and vehicle annual distance driven. The second approach is to use empirical, real-world, data to estimate the UF, which provides an insight into actual travel behavior patterns [15]–[20].

In both approaches, the studies referenced above focus solely on the PHEV, except the report of Nicholas et al. [20] which serves as a predecessor to our study. To our knowledge, there has not been any assessment of the UF on the household level – as the share of eVMT within total household miles traveled – that takes into account all vehicles in a household and captures the overall household electrification of miles. The goal of this study is to fill this gap and assess the UF within the household context and investigate how household factors impact eVMT, UF of the PHEV and UF of the household, using an empirical data set. We use data from 169 vehicles which had onboard loggers that recorded driving and charging data for a year, distributed among 71 households where each household had a PEV. Our dataset includes BEVs along with PHEVs, and the UF of BEVs is 1 by default since all of their traveled miles are electrified. On the household level, UF can be calculated for BEV-households — since each household owns only one PEV, they can be classified as either a BEV or PHEV household — and this enables us uniquely to compare the UFs of BEV-households and PHEV-households.

In this study, we use the following three main metrics in our analysis: eVMT, UF of the PEV and UF of the household. To set a limited scope for our analysis, we define the household context under these four categories: (1) PEV technology in the household, (2) household vehicle usage, (3) ICEVs in the household and (4) driver identity. We first identify the variables in our data set that we can label as factors corresponding to each of these categories. Then, we use descriptive statistics to explain how the most salient factors impact our main metrics. This is followed by a regression analysis for each of our main metrics where we investigate the statistical significance of the factors we identified. The outline of the paper is as follows: In Section 2, the data and methods are described. In Section 3, the results are presented. Section 4 contains the discussion and we close with the summary and conclusions in Section 5.

2 Data and Methods

The data we use is from Phase 1.0 of The Advanced Plug-in Electric Vehicle Travel and Charging Behavior Project which aims to provide an insight on how plug-in electric vehicles are used on a day to day basis within the household travel context by placing data loggers in participant households for a period of one year [20]. The project was initiated by the Plug-in Hybrid Electric Vehicle Center at University of California, Davis; thus we refer to this data set as the UCD data. Data was collected from summer 2015 to summer 2016, in California, USA, within 71 households by placing a monitor in all household vehicles except the ones driven less than 1000 miles per year. Participating households were selected in consultation with the California Air Resource Board to fit an appropriate sampling of the population. Odometer readings were taken from cars that were driven less than 1000 miles per year. Each household owns only one plug-in hybrid vehicle (PEV). Among the 71 households, 18 have a Toyota Plug-in Prius, 17 have a Ford C-Max/Fusion Energi, 18 have a Chevrolet Volt and 18 have a Nissan Leaf. Nissan Leaf is the only battery electric vehicle (BEV) in the data set, whereas the rest are plug-in hybrid electric vehicles (PHEVs). All PEVs in the data set are from the model year of 2013 or 2014. Dataset also includes an extensive survey made with the PEV owners prior to the placement of the monitors.

The raw data collected from the loggers and through the survey was cleaned by the Plug-in Hybrid Electric Center. We use three different sets of data in our analysis: trip data, charging data and survey data.

2.1 Provided Datasets

2.1.1 Trip Data

Trip data consists of each single trip that was made by the logged vehicle. The separating factor between trips was that the car remained at the same position idly with a speed of zero for at least 5 minutes. The dataset provides information regarding the start time and duration of the trip as well as the total distance travelled and fuel consumption during the trip. It also includes the electric vehicle miles travelled (eVMT) and gasoline vehicle miles travelled (gVMT) for each single trip. The calculation of eVMT and gVMT were performed by the Plug-in Hybrid Electric Vehicle Center and is not the main focus of this paper. eVMT calculation methods do not differ much from each other as other studies show, e.g. eVMT calculation based on label fuel economy versus vehicle average charge sustaining fuel consumption differs less than 2.5% in a study of Idaho National Laboratory [19].

The following variables were available in the dataset for each single trip.

Table 1: Variables in the trip dataset

Trip information	Trip Start Time, Duration, Trip Distance (km), Trip Distance (mi), Fuel Consumption (l), Fuel Consumption (gal), gVMT, eVMT, zVMT
Vehicle identification	Vehicle ID No, Vehicle Type (PEV or ICE), Year, Make, Model, Miles per Gallon
Logger information	Logger Installation Date, First Fleet Trip Date, First File Date, Logger Uninstall Date, Initial Odometer Reading, Final Odometer Reading, Odometer Reading at Logger Uninstall
Household identification	Household ID No, List of PEVs in the Household, List of ICEs in the Household, Number of Drivers, Number of Non-Drivers, Size of the Household, Number of Vehicles in the Household, Number of Logged Vehicles in the Household, Vehicle-Driver Ratio

2.1.2 Charging Data

Charging data consists of each single charging event performed by the logged vehicle. It provides information regarding the start and end times of the charging event, charge levels (either level 1 or level 2), start and end state of charges (SOCs) and current useable state of health (SOH) of the battery. Dataset also provides information about the location of the given charging event, in latitudes and longitudes. Furthermore, each charging location is classified as home, public or work.

The following variables were available in the dataset for each single charging event.

Table 2: Variables in the charging dataset

Charging information	Start Time, End Time, File ID, Start SOC (%), End SOC (%), Useable SOH, Charge Level, Charger Energy Non-Annualized, Charger Loss, Offset
Location information	Latitude, Longitude, Time Zone, Location (Home, Public or Work)

Identical to the trip dataset, charging dataset also contains information regarding vehicle & household identification and logger information, for this reason they are not shown in Table 2.

2.1.3 Survey Data

The survey was implemented and completed in April and May of 2015, prior to the placement of the monitors. The survey provides detailed information about the vehicles and inhabitants of each household, as well as the self-reported behavior of those inhabitants regarding charging, commuting and the effect of incentives in their decision-making to purchase or lease plug-in hybrid electric vehicles.

2.1.4 Other Sources of Information

The range of the PEVs we use in our analysis are based on the information provided by the U.S. Environmental Protection Agency; which is 11 miles for Toyota Prius, 20 miles for Ford Energi, 36 miles for Chevrolet Volt and 80 miles for Nissan Leaf.

2.2 Compiled Dataset for Analysis

From the datasets provided by the Plug-in Hybrid Electric Vehicle Center, we selected and computed the following variables that we labeled as factors corresponding to the categories of the household context.

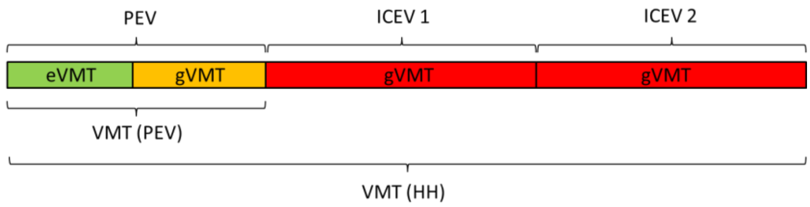
For the category of PEV technology in the household, we have selected the variable *range* and computed the variable *frequency of charging*. *Range* is defined as the all-electric range of the plug-in electric vehicle of that household. *Frequency of charging* is defined as the average number of charging events per day for the plug-in electric vehicle of the given household. In our analysis we have used *frequency of charging* without making any distinctions between charging locations; however, in order to figure out if charging location had any impact on our results, we also have computed 3 different variations of this variable: frequency of charging at home, at public and at work.

For the category of household vehicle usage, we have selected the variable *number of drivers*, and computed the variables *commute distance*, *frequency of overlaps* and *frequency of long-distance trips*. *Commute distance* is defined as the distance between home and work travelled with the PEV and is based on the survey data. Each respondent was asked if they commute with the PEV in the household. If the response was positive, they were asked to provide the location and thus the commute distance was calculated. If the response was negative (non-commuters), then the distance for the most frequent weekday trip was assigned as the commute distance for that PEV. If the respondent did not answer that part of the survey, we assigned zero for the commute distance. Out of 71 households, 9 were non-commuters, meaning none of the people in the household commuted, and only 3 did not answer the relevant question in the survey. *Frequency of overlaps* is defined as the percentage of PEV trips that overlap with any of the ICEV trips in that household. *Frequency of long-distance trips* is defined as the percentage of single trips (not daily) made by the PEV that are above 50 miles. We have also computed the *frequency of long-distance trips* where the threshold was respectively 20, 30 and 40 miles, in order to see how the definition of a long-distance trip would impact our results.

For the category regarding the ICEVs in the household, we have computed the variables *size of ICEVs in the household* and *MPG of ICEVs in the household*. Both variables are derived from the survey data. *Size of ICEVs in the household* is defined as a dummy variable that returns 1 if the smallest car in the household is larger than the PEV and 0 otherwise. In order to test for the sensitivity of our definition, we have also tested a dummy variable for the same purpose that returns 1 if the largest car -as opposed to the smallest before- in the household is larger than the PEV and 0 otherwise. *MPG of ICEVs in the household* is defined as the weighted average of miles per gallon of ICEVs in the household where the weight coefficient is calculated as the percentage of the actual usage time (hours) of the given ICEV among all the ICEVs in the household.

For the category regarding the driver identity, we have selected the variable *share of PEV usage of the main driver* which is derived from the survey data. It is defined as a percentage showing how much of the time the main driver of the PEV uses the vehicle in that household.

We have computed the following dependent variables for our analysis: *eVMT*, *utility factor of the PEV* and *utility factor of the household*. *eVMT* is defined as the annualized electric vehicle miles travelled by the given PEV in the household. *Utility factor of the PEV* is defined as the share of eVMT within the VMT of the PEV. Finally, *utility factor of the household* is defined as the share of eVMT within the VMT of the household, all vehicles considered. In our annualization, we have used the first and last recorded trip for that vehicle. See Figure 1 for a sample distribution of vehicle miles travelled in a household with 1 PEV and 2 ICEVs.



$$\text{UF (PEV)} = \frac{eVMT}{VMT(PEV)} \qquad \text{UF (HH)} = \frac{eVMT}{VMT(HH)}$$

Figure 1: Distribution of vehicle miles travelled in a household with 1 PEV and 2 ICEVs

For each of the 71 households, all the variables that we have selected or computed are summarized in Table 3 below.

Table 3: Variables in our compiled dataset

Dependent variables	eVMT, Utility Factor of the PEV, Utility Factor of the Household
Independent variables	Range, Frequency of Charging, Number of Drivers, Commute Distance, Frequency of Overlaps, Frequency of Long-distance Trips, Size of ICEVs in the Household, MPG of ICEVs in the Household, Share of PEV Usage of the Main Driver

2.3 Methods

We have used descriptive and inductive statistical methods, and regression analysis on our compiled dataset in order to assess the eVMT and the UF within the household context; descriptive statistics to see the household level in more detail, and the regression analysis to provide a helicopter view and explain overall trends.

Below is our generic regression model where we use the same independent variables for all:

$$\begin{aligned} Y_i \; = {} & \beta_0 + \beta_1 Range_i + \beta_2 Number\ of Drivers_i + \beta_3 Commute\ Distance_i \ + \beta_4 PEVShare_i + \\ & \beta_5 FreqCharging_i + \beta_6 FreqLongdistance_i \ + \beta_7 FreqOverlaps_i \ + \ \beta_8 ICEVSize_i + \\ & \beta_9 ICEVMpg_i + \varepsilon \end{aligned} \qquad (1)$$

$$i = \{1, \ldots, 3\}\ where\ Y_1 = eVMT, \qquad Y_2 = UF\ of\ the\ PEV, \qquad Y_3 = UF\ of\ the\ household$$

We performed multivariate regression analysis on eVMT and logistic regression on UF of the PEV and UF of the household since the utility factor is always between 0 and 1. In the regression analysis of UF of the PEV, 18 households which had a Nissan Leaf as the PEV were removed from the dataset for analysis, since Nissan Leaf is a battery electric vehicle and therefore would result in a UF (PEV) of 1 at all times.

3 Results

3.1 Descriptive Statistics

Summary statistics of all the households are provided in Table 4. It consists of seven of the nine factors, plus the *number of vehicles* as an additional variable. The two factors that were not included are *range* which only has four variations based on the PEV type, and *size of ICEVs in the household* which is a dummy variable. We observe that there are more vehicles than drivers overall. Frequency of charging is similar for all PEVs with a mean of 0.80.

Table 4: Summary statistics of all households

	Min	0.25-quantile	Median	Mean	0.75-quantile	Max
All households combined (N=71)						
Number of drivers	1	2	2	2.01	2	5
Number of vehicles	1	2	2	2.42	3	5
Commute distance	0	4.2	12.1	17.9	24.7	128.6
Share of PEV usage of the main driver	50%	81%	90%	88%	100%	100%
Frequency of charging	0.04	0.61	0.77	0.80	0.97	1.96
Frequency of long-distance trips	0%	0%	1%	2%	2%	23%
Frequency of overlaps	0%	0%	3%	4%	5%	16%
MPG of ICEVs in the household	0	0	20	18.4	25.6	50

Utility factor of the household makes it possible to make comparisons between households with different number of cars and also between PHEV households and BEV households. As seen in Figure 2, utility factor of the households has a downward trend when the number of cars increases. In other words, households with more cars electrify a lower share of their total travelling, which is expected because households with more cars also drive more in total as seen in Figure 3. This trend applies to almost all PEV-types, with the exception of a few five-car households which are not visible in Figure 2. We observed that in two of the five-car households (both are Volt households), there is a sharp increase in the utility factor of the household which contrasts with the rest of the data set. After further investigation into these households —of which there are only two— to see why they behave differently, it was found out that they have a high number of unused cars. While both households have five cars in total, they only use two of them regularly and the remaining three stay idle. Thus, although they are registered as five-car households, they behave as two-car households, which puts them in line with the rest of the data set.

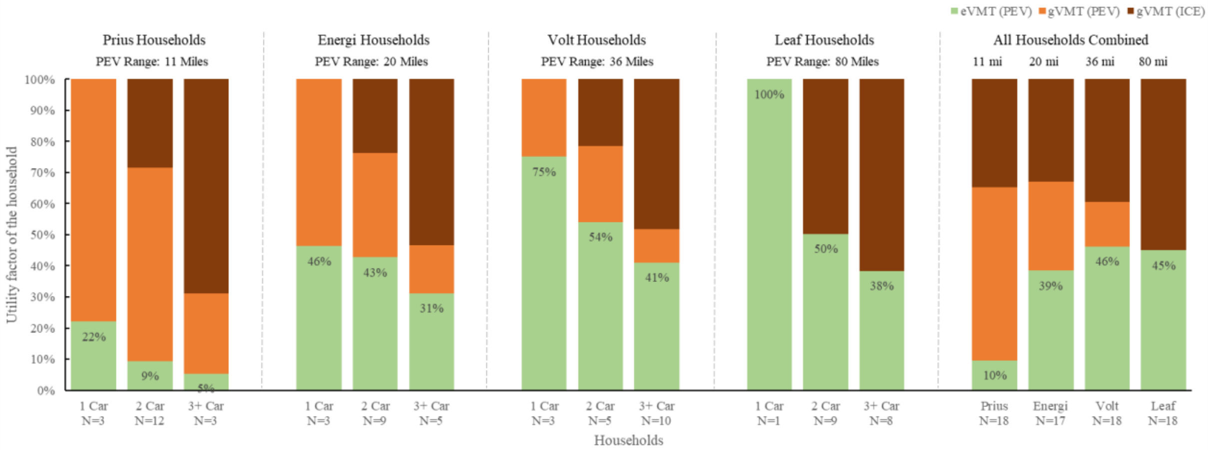


Figure 2: Utility factor of households, categorized by PEV-type and total number of cars in the household

Combining same-PEV households and observing their utility factor provides quite interesting results. Among the PHEVs, Volt households have the highest utility factor, followed by Energi and Prius households. Considering that Volt has the longest all-electric-range, again followed by Energi and Prius, we can conclude that households that have PHEVs with higher ranges end up electrifying a larger share of their total miles. When we compare Leaf households, which are the only BEV households in our data set, with the other three PHEV households, we see very surprisingly that Volt households have a higher average utility factor (UF of the household) in total at 46% than Leaf households at 45%. This finding shows that, in the context of the entire household, a PHEV like the Chevrolet Volt with half the range of a BEV like the Nissan Leaf, can electrify almost the same share of miles, if not more.

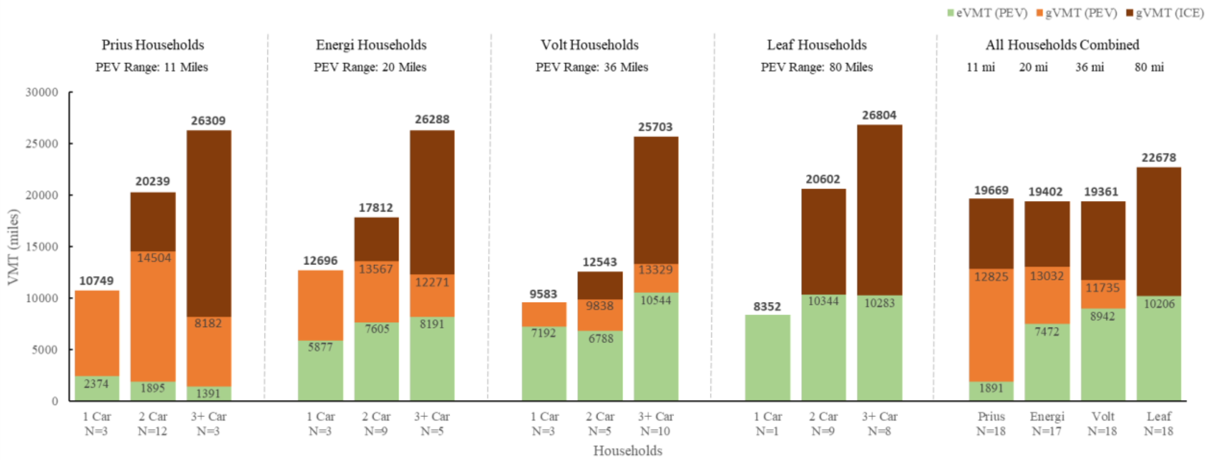


Figure 3: VMT of households, categorized by PEV-type and total number of cars in the household

Total annual household VMT among PHEV households are very similar as seen in Figure 3 and range from 19,361 miles for Volt households to 19,669 miles for Prius households. We observe that BEV households, on the other hand, have a slightly higher annual total VMT. Prius households have an annual eVMT of 1,891 miles and PEV VMT of 12,825 miles, thus placing their UF of PEV at 15%. Energi households have an annual eVMT of 7,472 miles and PEV VMT of 13,032 miles, placing their UF of PEV at 57%. Volt households have an annual eVMT of 8,942 miles and PEV VMT of 11,735 miles, placing their UF of PEV at 76%. This finding suggests that there is a trend where the UF of a PHEV increases with range. In Figure 4, we compare the eVMT and UF of PEV from our dataset with the data of Idaho National Labs (INL) [19] for the same set of cars with the same set of all-electric-range. Note that the INL data has two versions of Ford Energi (C-max and Fusion) whereas our data identifies them as one model. Although the number of vehicles in the INL's dataset are in the thousands compared to our relatively small sample size of 71, eVMT and the UF of the PEV we estimated match with INL's estimates, with the exception of Ford Energi, seen in the figure at the 20-mile range. The exact reasons of this discrepancy are not known to us, but we find it noteworthy to say that this does not in any way decrease the significance of range in our findings.

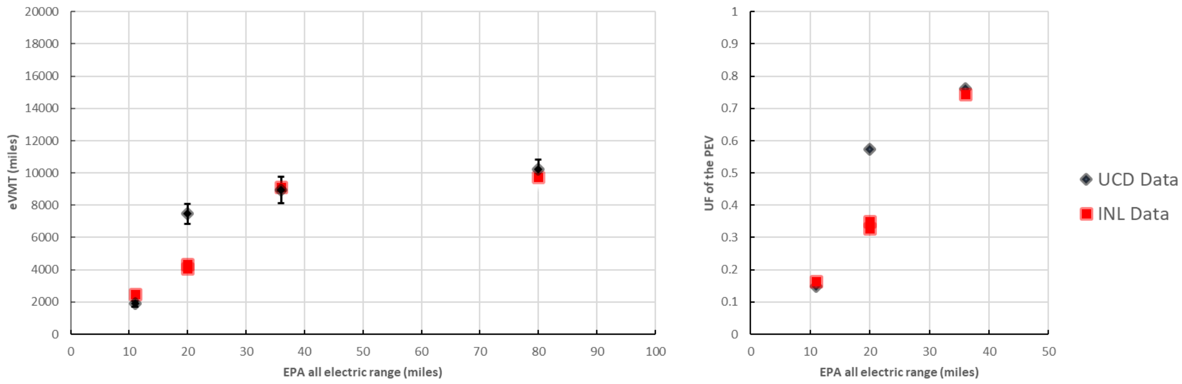


Figure 4: Mean annual eVMT and UF of PEVs vs. range (UCD and INL data)

The impact of frequency of charging on eVMT, UF of the PEV and UF of the household can be seen in Figure 5 with linear best-fit lines. There is an overall trend that higher frequency of charging results in higher eVMT, UF of the PEV and UF of the household. This trend is especially more visible for eVMT of Volts and Leafs where we observe a steeper best-fit line compared to Prius and Energi.

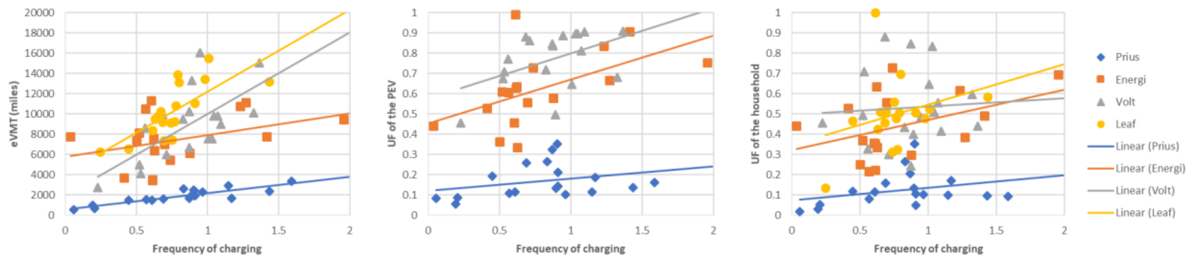


Figure 5: Mean annual eVMT, UF of the PEV, UF of the household vs. frequency of charging

3.2 Regression Analysis

Results of the regression analysis for each of our main metrics are given in Table 5. Note that a multivariate regression was performed on eVMT and a logistic regression was performed on UF of the PEV and UF of the household. Logistic regression on UF of the PEV excludes Leaf households, since their utility factor is always 1.

Table 5: Regression results for eVMT, UF of the PEV and UF of the household

Dependent:	eVMT		UF of the PEV		UF of the hh	
Intercept	-2073		-0.334		0.310	.
	(3318)		(0.209)		(0.182)	
Range	93.97	***	0.023	***	0.004	***
	(14.26)		(0.002)		(0.001)	
Number of drivers	404.60		0.066		-0.047	
	(565.10)		(0.040)		(0.031)	

Commute distance	26.83		0.001		-0.002	
	(23.53)		(0.001)		(0.001)	
Share of PEV usage of the main driver	1187		0.136		0.063	
	(2809)		(0.180)		(0.154)	
Frequency of charging	3885	***	0.152	*	0.173	**
	(1092)		(0.064)		(0.060)	
Frequency of long-distance trips	10180		-1.940	**	0.040	
	(12320)		(0.715)		(0.675)	
Frequency of overlaps	9058		-1.047		-1.458	*
	(1120)		(0.659)		(0.604)	
Size of ICEVs in the household	-515.5		0.019		-0.049	
	(763.7)		(0.047)		(0.042)	
MPG of ICEVs in the household	0.008		0.001		-0.004	*
	(30.760)		(0.002)		(0.002)	
Multiple R-squared	0.545		-		-	
Adjusted R-squared	0.478		-		-	
Confidence levels	*** %99.9, **%99, *%95, .%90					
Values represent estimates, standard error is given in parentheses.						

Our results show that range is statistically very significant in the electrification of miles, and higher ranges result in higher eVMT, UF of the PEV and UF of the household. This result confirms the initial trend we had observed in Section 3.1 and is also in line with the findings of previous studies [5], [13], [14].

Frequency of charging is also statistically significant, showing up in all of our main metrics. This result also confirms the trend that we had observed in Section 3.1. This suggests that more frequent charging results in higher eVMT, UF of the PEV and UF of the household. However, it should be noted that the frequency of charging is based on the number of charging of events in this study and not the length of these charging events; in addition to that, the charging level is not taken into account. With regards to developments in charging infrastructure, more charging points might increase the frequency of charging.

Frequency of long-distance trips is statistically significant for the UF of the PEV. The results show that more frequent long-distance trips decreases the UF of the PEV, without having any impact on eVMT. This suggests that the decrease in UF of the PEV can only be explained by the increase in gVMT of the PEV, meaning a lower fuel economy as long-distance trips become more frequent. Plötz et al. [5] also reached the same conclusion in their paper on the impact of daily and annual driving on fuel economy, where they conclude that tendency for long-distance trips decreases the fuel economy and UF of a PHEV.

Commute distance is not statistically significant for any of our metrics. Based on our findings regarding the frequency of long-distance trips and the intuitive assumption that higher commute distances would behave similar to frequent long-distance trips, our expectation was to find a statistically significant relationship between commute distance and UF of the PEV. However, to our surprise, our results show that commute distance has no influence on neither the eVMT nor the UF of a PEV. The reason for this result might be that the commute distances in our dataset do not have enough variation to result in a difference between short and long commute distances.

Frequency of overlaps is statistically significant for the UF of the household. As expected, more overlaps between PEVs and ICEVs result in higher ICEV usage which increases the gVMT and VMT of the household and thus lowers the UF of the household. Our results also show that the higher the MPG of ICEVs in the household, the lower the UF of the household is. MPG of ICEVs in the household does not have a statistically significant relationship with the eVMT, therefore an explanation for the reduction in UF of the household is that these ICEVs replace trips that would otherwise be done with the PEVs. This suggests that ICEVs with higher MPGs have a higher likelihood to replace trips from the PEV in the household.

Number of drivers do not seem to be statistically significant for any of our metrics, suggesting that the ratio of PEV trips to ICEV trips stay relatively similar regardless of the number of drivers in the household, and a higher number of drivers does not lead to more use of ICEVs. The size of ICEVs in the household and the share of PEV-usage of the main driver were also found to be non-significant for all our metrics, the latter suggesting that shifting between drivers within the same household has no impact on neither eVMT nor any of the UFs.

4 Discussion

Like all datasets, our dataset also had its limitations. First of all, the sample size of our data was limited to only 71 households which put us at a disadvantageous point for performing regression analysis; however, it was collected for the length of a year and including ICEVs contained a total of 169 vehicles, which in our opinion strengthens our results. We consider this a trade-off that often arises between larger sample sizes with shorter lengths of measurements and small sample sizes with longer lengths of measurements. In Section 2, where we identified variables to label as factors corresponding to the categories of the household context, we considered more variables than what is presented. Some of the variables we considered included the size of the household, whether a charger was present at work and age of the PEV users. We run our preliminary regression models with those variables included; however, we estimated variance inflation factors to check for multicollinearity and run likelihood ratio tests to see if our models were better off without those variables, and removing those variables made our models more robust, so we decided to omit them. The regression models we present in this paper have variance inflation factors lower than 2 for all variables.

Furthermore, as an additional measure to make our models more robust, we have tested several different variations of some variables. For the frequency of charging, we tested three different variations where the location was limited to only home, only work or only public. In our analysis, these three variations fell short of explaining the UF of the PEV and UF of the household; so instead we decided to estimate frequency of charging regardless of the location. For the frequency of long-distance trips, we considered trips over 50 miles in our models, but we have also tested three different variations where we set the threshold at 20, 30 and 40 miles. A higher threshold increased the statistical significance of the variable; thus, we decided to use 50 miles as the threshold for long-distance trips. For the size of ICEVs in the household, we tested a slightly different variation where we compared the largest car in the household to the PEV instead of the smallest car, and our testing showed that comparing the smallest car yielded more significant results for the variable. For the MPG of the ICEVs in the household, we tested for weighted and unweighted average MPG of ICEVs, and the weighted average MPGs resulted in a higher statistical significance for the coefficient.

Our dataset is regionally bound to California and the households that were included could be considered as early adopters, with higher education and income levels. 54 of the 71 households in our dataset had an annual income of over $100,000, and 61 out of the 71 people who were interviewed had at least a college degree with 39 having a masters, doctorate or a professional degree. We recognize that this might have created a bias towards more conscious driving and charging behavior, and our results might have differed slightly if a larger and geographically more diverse population sample was used. However, California is one of the leading EV markets and at the time of the data collection for this study, California was at the initial stages of the early adopter group among the consumer categories of technology adopters [21]; therefore, we consider these limitations inevitable.

Our finding that a higher all-electric-range results in a higher UF for a PHEV has been repeatedly reported in the literature [5], [13], [14]. Our results showed that this also holds true for the UF of the households that have a PHEV. Estimating UF of the household has also enabled us to compare PHEVs and BEVs, and this led to the interesting finding that in the context of the household a PHEV such as Chevrolet Volt with half the range of a BEV such as Nissan Leaf can have a higher UF. However, this finding should be interpreted with a grain of salt, because we only had one BEV model to compare our PHEVs with and apart from Chevrolet Volt, our other PHEVs were all low-range PHEVs; therefore, we didn't have enough variation among our PEV models to come to a solid conclusion. In addition, as mentioned in Section 3.1., BEV households in our dataset had much lower shares of long-distance trips and drive around 2,000 more miles annually compared to PHEV households, which suggests that they are using ICEVs for long distance trips, which lowers the UF of the household. Therefore, the reason behind the low UF of BEV households might be the low all-electric-range (AER) and the range limitation that comes with it. PEV market is a fast-changing market and later model PHEVs and BEVs all have higher AER than the vehicles in our study, for instance a Nissan Leaf model with a higher AER that is also used for long-distance trips could result in different UFs in the household context.

5 Summary and Conclusions

In this paper, we used a dataset of 71 households where each household had one PEV and analyzed through descriptive statistics and regression analysis how factors within the household context impact eVMT, UF of the PEV and UF of the household. Our results indicate that a PHEV with a higher all-electric-range results in more electrification and thus a higher UF for both the PHEV and the household. Furthermore, our results show that —considering the UF of the household— a PHEV like the Chevrolet Volt with half the range of a BEV like the Nissan Leaf can electrify the same share of miles if not more within the household context. However, we consider this trend to apply only to low range PHEVs and BEVs like in our dataset, because we attribute this result to the low range of Nissan Leaf in our study and the range limitation that comes with it. Our results also indicate that more frequent charging results in higher electrification of miles and a higher UF for both the PHEV and the household. However, it should be noted that we did not take charging duration into account. In addition, our results show that more frequent long-distance trips result in lower UF for the PHEV. Equally important, our results suggest that, within a household, ICEVs with higher MPGs have a higher likelihood to replace trips from the PEV and consequently lower the UF of the household.

Concluding, our results provide an insight into the electrification of vehicle miles travelled within the household context which is rarely taken into consideration. The implication for policy makers is that PHEVs with a range of at least 36 miles have the potential to electrify a similar share of total household miles as some BEVs and thus can play an important role in decarbonizing the transport sector.

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