Coming of Age: Understanding Electric Vehicle (EV) Use Over Time via Used Vehicle Market Data

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Executive Summary

The majority of existing research on plug in electric vehicles (PEVs) focuses on new vehicle market dynamics. We provide the first high resolution, nation-wide estimates of PEV mileage in the United States. Previous estimates are based on limited or outdated data that indirectly measure mileage via surveys or household energy use data. We directly measure mileage from odometer readings from over 36 million used vehicle listings at over 60,000 dealerships in the US, comparing conventional, hybrid (HEV), plug-in hybrid (PHEV), and battery electric (BEV) vehicles. While HEVs and PHEVs are driven comparably to CVs, BEVs are driven significantly less, with BEV cars traveling on average 3,300 fewer miles per year. Teslas are driven significantly further than other BEVs, with 1,874 more miles on average per year. The effect of driving longer driving ranges is significant for Tesla BEVs but not other BEVs. Our results indicate that while current BEVs are not being driven as much as conventional vehicles, they approach parity under conditions that already exist for some BEVs in some locations.

Keywords: Electric Vehicles, Used PEVs, Miles Driven, Powertrain, Vehicle Age, Mileage, Behavior

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1 Introduction

As more and more vehicles transition from gasoline and diesel energy to electric energy, utilities are responsible for providing more and more of transportation's energy. So far, most work on PEV adoption has focused on the rate of new PEV purchases, but as they become increasingly mainstream, studying the dynamics of the used PEV market will become essential to accurately planning PEV energy and power needs. Understanding adoption trends and behavioral patterns as vehicles age will be especially important in increasing PEV adoption among mainstream vehicle buyers. Key stakeholders, including utilities, car and charger manufacturers, and community organizers will be interested to know where most new and used PEV adoption will take place and how overall miles driven in PEVs compares to CVs. In the long run, understanding how PEV drivers live with, use, and ultimately separate with their vehicles better prepares utilities and the multitude of other PEV-oriented industries towards this shift in transportation. This collaborative effort between Electric Power Research Institute (EPRI) and researchers at George Washington University (GW) characterizes PEV usage over time through analysis of industry-leading data.

2 Main

Plug-in electric vehicles (PEVs) are critical alternatives to gasoline-powered conventional vehicles (CVs) but reaching mass PEV adoption depends on how well the technology performs as a direct substitute for CVs [1]. Vehicle mileage is a useful metric for making that assessment; if PEVs are driven as much as CVs, their potential as a substitute is promising, but if they are driven less, it calls into question whether the technology (and/or related infrastructure, etc.) is ready to serve the needs of all CV drivers. Having an accurate measurement of PEV mileage is also important for utilities, policy makers, planners, and other industry stakeholders. Mileage estimates are a fundamental input to energy models used to project future electricity demand from PEV charging. Furthermore, having an accurate estimate of PEV mileage could become important for government budget planning as scholars are increasingly calling to replace the gasoline tax with a vehicle mileage tax [2][3][4].

Despite the significance of such an important metric, prior published estimates of PEV mileage have conflicting results, concluding that battery electric vehicles (BEVs) are driven as little as 5,300 miles [5] and as much as 10,230 miles annually [6]. The inconsistency in prior mileage estimates is rooted in data limitations. Most studies indirectly measure mileage by using surveys of vehicle owners [7][6] or by examining the increased electricity use in households that adopted a PEV [5] but these approaches have suffered from multiple factors, such as the indirect nature of the measurement, small sample sizes, or unrepresentative samples (e.g. limited to specific regions such as California). The few studies that have directly measured mileage using on-board vehicle data loggers also suffer from unrepresentative, limited sample sizes and limited time frames [8][9][10]. No prior study has used nation-wide data with sufficient sample sizes to quantify the heterogeneity in PEV mileage to understand under what conditions it differs from CV mileage.

This study overcomes many of these data challenges by using odometer readings collected from a large data set of used vehicle listings in the United States. The dataset includes over 36 million observations from cars and SUVs listed at over 60,000 dealerships between 2016 and 2022, providing an unprecedented high-resolution lens into the vehicle miles travelled (VMT) across multiple powertrains and multiple years. By combining the odometer readings with other data on vehicle specifications and environmental data, we are able to quantify the heterogeneity in revealed VMT and identify under what conditions PEVs are driven more similarly to CVs. Our results indicate that while current BEVs are not being driven as much as CVs, they approach parity under conditions that already exist for some BEVs in some locations, such as higher-range BEVs and Tesla BEVs in locations with higher gasoline prices.

2.1 Adoption and Retention Decisions

Little is known about how consumers choose to adopt a used PEV or the dynamics of when individual vehicle owners choose to sell or retire their vehicle. Understanding how household characteristics may affect likelihood of PEV adoption is important, because it will help utilities and other stakeholders plan for the increase in energy demand. Various consumer characteristics are influential in determining the likelihood of adopting a used PEV or not. For example, as of 2015, low-income consumers were less likely to buy an PEV than high-income households. However, if they did buy an PEV, it was more likely to be used [30]. Additionally, incentives may have a significant impact on where PEVs are adopted. For example, when Illinois, Tennessee, and Georgia dropped their PEV incentives ranging from $2,500 and $4,000 between 2011 and 2015, PEV registrations rapidly fell [11] as PEVs are more expensive to purchase than their ICEV analogues [12]. As depreciation and other factors lower the entry price of PEVs, lower-income communities will be more likely to adopt these vehicles.

3 Measuring Vehicle Mileage

Several studies have examined differences in vehicle miles traveled (VMT) for different vehicle powertrains. However, both direct and indirect methods of measurement have generated a wide range of estimates with little consistency. Nonetheless, most scholars expect that BEVs may have lower VMT than that of CVs due to their limited driving ranges and the behavioral issue of "range anxiety" associated with it, which has been shown to be a major factor in affecting driving patterns [13] [14][15]. In addition, the majority of early BEV adopters own more than one vehicle [9][16][7]. As a result, these owners may choose to drive their BEV less, substituting it with a CV for longer trips.

One common source of data is to collect a large-scale dataset is via household surveys, such as the National Household Travel Survey (NHTS) [17][18][7]. The NHTS survey results suggested that BEVs are only driven approximately 66% as much as CVs on an annual basis [17]. Nonetheless, despite the survey's nationwide reach, only 436 responses were obtained from BEV owners, and the survey data (from 2017) is now relatively outdated. As a result, the relatively low BEV mileage estimates from these data may be lower than how BEVs are driven today. As seen in Figure 2, earlier generations of BEVs had significantly shorter driving ranges than today's BEVs [7], and because the earlier generation of BEV owners may have substituted trips with an additional household CV [9] [16] [7].

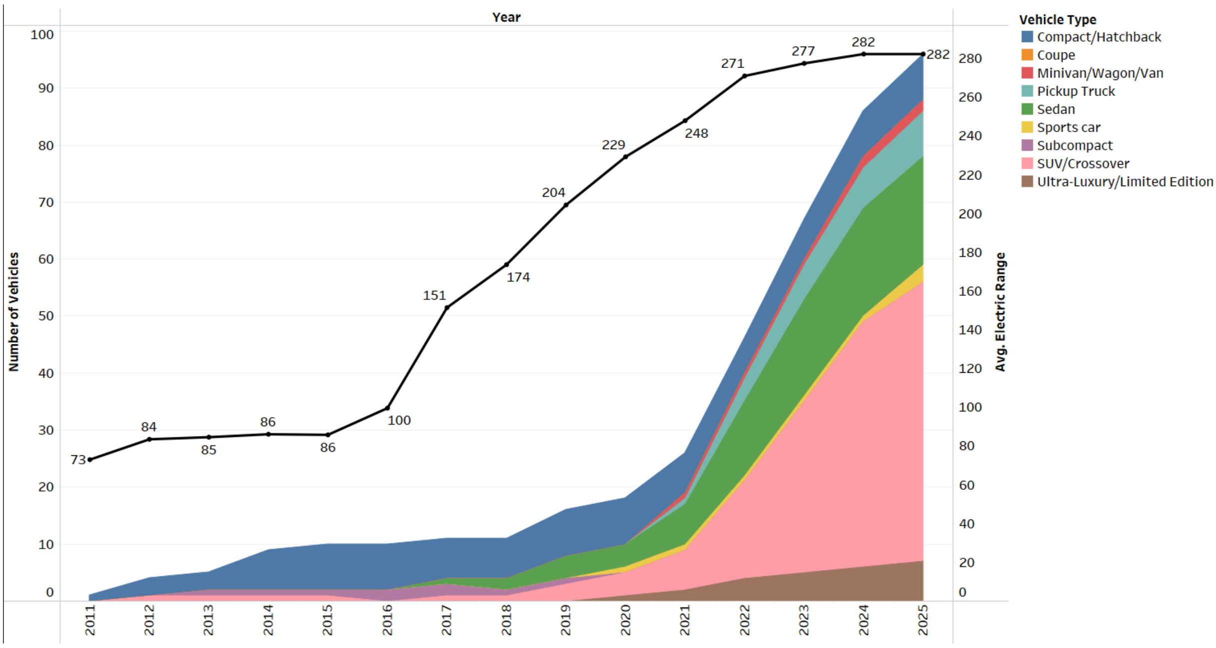

Figure 2: Proportion of Vehicle Types and Average Electric Range [31]

Another indirect approach to estimate VMT is to extrapolate it from related data sources, such as electricity meter readings. Burlig et al. (2021) collected home meter readings from 2014 to 2017 in California and combined it with vehicle registration data to create a sample with 57,290 BEVs—the largest-scale sample of BEVs in a related study to date. Using a discrete event approach, they analyzed the increased electricity consumption after household purchased a BEV and then extrapolated the electricity into expected VMT. Their results suggested BEVs were driven 5,300 miles on average annually. While this estimate is consistent with other findings that BEVs are driven less than CVs, these results heavily rely on charging pattern assumptions, and it is certainly plausible that it underestimates the true VMT as BEV owners could have re-charged their vehicles away from their homes [19][5].

To overcome the potential biases from indirectly measuring mileage, some researchers have used on-board vehicle sensors to get real-world data directly from vehicles to examine usage patterns [20][9][10] [21] [22]. One example is the detailed analysis by Tal et al. (2020) on the driving patterns of BEV and PHEV owners in California. In this study, survey questionnaires were distributed among 10,000 California households, filtering for suitable vehicle-related criteria, and 264 households were selected to install onboard loggers in their PEV. After collecting data for one year, the average annual VMT for BEVs was 12,522 miles—nearly double the estimate from Burlig et al. (2021) for California BEV owners in the same time period. The study also concluded that BEVs with higher ranges were driven further than those with lower ranges and that BEV owners tended to substitute longer-distance travel with CVs [6]. Nonetheless, the final sample at the conclusion of the study only included about 100 BEVs – comparatively small sample with little variety in vehicle models. Given the excessive cost of such direct measurement, increasing the sample size to obtain a representative sample is infeasible. Similar studies that use sensors to directly measure mileage also found higher BEV VMT than the studies that indirectly measured VMT, but they also suffered from small sample sizes [8][9][10]. Table 1 summarizes these prior studies and their estimated electric VMT (eVMT) for BEVs.

In general, previous studies on understanding eVMT failed to estimate/measure eVMT from an at-scale, generalizable and up-to-date sample. Scaling the model up with a larger sample is difficult due to multiple factors such as cost considerations, fast technology iteration rates and the conditions of an early-stage market. With important topics such as tax reform [2] and measuring a BEV's social and environmental impact [23], it is critical to have a clear understanding on how BEVs are being used and gain insight into drivers' behaviors. In this study, we utilized first at-scale and up-to-date dataset on U.S. auto fleet to provide a clear estimation on eVMT and provide important insight on factors that affect BEV driver's behaviors.

Study	Estimated Annual eVMT	Sample Location	Sample Size (BEVs)	Data Year(s)	Data Source
Davis (2019)	6,300	US	436	2017	NHTS*
Tal et al. (2020)	12,522	California	100	2015 - 2018	On-board vehicle sensors
Burlig et al. (2021)	5,300	California	57,290	2019	Household electricity meter readings
Jia and Chen (2022)	10,000	California	184	2019	2019 California Vehicle Survey
This Study (2023)	7,450	US	174,132**	2016 - 2022	Used vehicle listings (marketcheck.com)

*National Household Travel Survey

**Sedans only

Table 1: Summary of estimated eVMT from previous studies

3 Modeling vehicle mileage

In this study, we gathered nationwide vehicle listings data from *marketcheck.com*, a market research firm that scrapes individual dealership websites for daily vehicle listings. The raw dataset contains over 36 million used vehicle listings (20,647,760 cars and 16,080,259 SUVs) listed at 66,641 dealerships between January 2016 and February 2022. The listings data include the listing date, the dealership address, and key information about the vehicle, such as make, model, trim, model year, listing price, powertrain, and – most crucially – the odometer reading. After cleaning the data to remove duplicate listings there are 48 million new and used listings: 28,841,825 CVs, 952,126 hybrid, 190,867 PHEVs, and 272,126 BEVs.

	BEV	PHEV	Hybrid	CV
Miles (1,000)				
min	0.101	0.101	0.101	0.000
max	300.000	300.000	293.176	278.521
mean	53.362	60.519	39.880	27.485
sd	37.889	42.240	24.748	17.913
Age (years)				
min	1.000	1.000	1.000	0.003
max	16.000	16.000	11.222	13.816
mean	4.729	5.047	3.918	3.818
sd	3.020	3.013	1.596	1.604
Price (USD)				
min	1,895	2,991	1,599	2,053
max	111,556	43,900	154,900	19,8000
mean	15795.97	15038.72	20139.01	27559.70
sd	7681.049	5452.760	13662.646	20783.245
Range (miles)				
min	73			
max	405			
mean (sd)	165.828			
sd	85.707			

Table 2 summarizes several summary statistics by powertrain.

To examine VMT, we first compared the total VMT against vehicle age for each listing. Figure 1 presents a summary of these data where the median (solid lines) and interquartile ranges (bands) were computed for all listings in each month of age versus the total vehicle mileage. It is clear from the chart that hybrid and PHEVs accumulate miles at a relatively similar slope to CVs, but throughout the lifetime of the vehicle, BEVs are driven significantly less each year, a finding consistent with many previous studies [17][5][8].

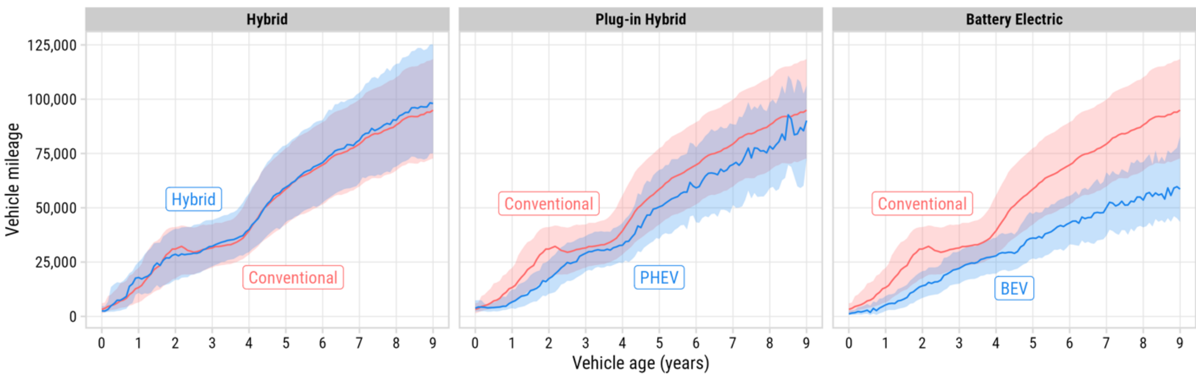

Figure 3: Comparison of the interquartile ranges of annual VMT by powertrain. Solid line shows the median range by age and bands reflect the 25th and 75th percentiles. Same curve for CVs in red for each sub-figure.

To quantify this difference, we first estimate a linear model of mileage versus age for each powertrain. Since the PEV market has a limited variety of SUV models, we have limited the scope of this study to sedans. Sedans are usually driven significantly less than trucks or other large SUVs. Along this vein, the lack of electric SUV options in the observed period may be biasing the VMT of PEVs down. We limit some of the potential bias by comparing PEVs solely to their CV sedan counterparts. To estimate the model, we treat each listing as an independent observation and feed those data into following Model 1:

$$mileage = \beta_0 + \beta_1 age + \beta_2 powertrain + \sigma age * powertrain + \sigma_2 age^2 * powertrain + \epsilon_i$$

From Model 1, the interaction effect between age and powertrain provides an estimate of the difference in annual mileage between CVs and other powertrains. The model result is presented in Figure 2. For CVs, VMT increases on average by 9,926 miles per year, and hybrids (10,370 miles annually) and PHEVs (10,011 miles annually) have similar results to CVs. BEVs, on the other hand, only accrue 6,926 miles per year, which is approximate 30% less than CVs. Although this result is consistent with studies that conclude eVMT is much lower than CV VMT, it is still higher than the NHTS survey results (Davis,2019) and the Burlig et al. (2021) results, which each underestimate this number by 1,000 and 2,000 miles per year, respectively.

Based on Alberini et al., (2021) study on NHTS data, age also affects VMT in a non-linear fashion. For Model 2, we account for this non-linear effect which yields several significant insights into how BEVs are being used in general. With the baseline aging effect of 9,926 miles per year, we observe a moderate non-linear aging effect. The negative sign for the age squared term of the BEV estimator indicates that the aging effect has a slightly diminishing slope with age. A further comparison with the aging effect among other powertrains reveals a much larger diminishing effect, a -0.125 difference between BEV and PHEVs, respectively. In other words, the annual VMT for BEVs decline more quickly compared to that of PHEVs. There are very few observations for BEVs, PHEVs and Hybrids that are more than 9-years-old. However, BEVs are more similar to CVs in their significant diminishing return. A plausible reason behind this is that the infrastructure around BEVs is still improving and has yet to reach an optimal level. BEV drivers also gain experience over time and may be more willing to drive further with experience. Thus, newly purchased BEVs are inclined to be driven more compared to their older models.

	Model 1	Model 2
(Intercept)	9.728***	0.423***
	(0.009)	(0.016)
age_years	9.226***	13.136***
	(0.002)	(0.006)
powertrainhybrid	-1.546***	1.862***
	(0.052)	(0.093)
powertrainphev	-9.065***	-2.480***
	(0.156)	(0.332)
powertrainbev	-8.670***	-4.451***
	(0.135)	(0.277)
age_years:powertrainhybrid	1.144***	-0.328***
	(0.009)	(0.033)
age_years:powertrainphev	0.785***	-1.787***
	(0.037)	(0.149)
age_years:powertrainbev	-2.300***	-3.707***
	(0.032)	(0.123)
age_years^2		-0.292***
		(0.000)
powertrainhybrid:age_years^2		0.106***
		(0.002)
powertrainphev:age_years^2		0.151***
		(0.015)
powertrainbev:age_years^2		0.026*
		(0.013)
Num. obs.	30250615	30250615
R^2 (full model)	0.543	0.551
R^2 (proj model)		
Adj. R^2 (full model)	0.543	0.551
Adj. R^2 (proj model)		

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 3: Annual Mileage by Powertrain

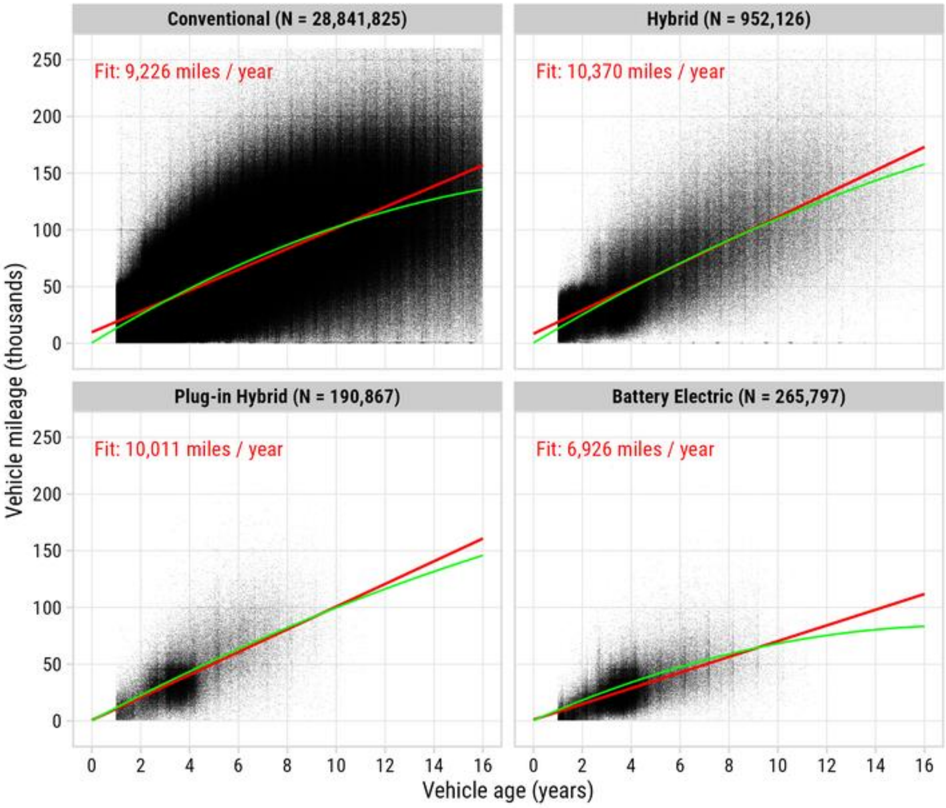

Figure 3: Scatterplot of annual vehicle mileage (thousands of miles) versus age (years) for four vehicle powertrains. The red line is the best fit linear model for each powertrain.

To explore the heterogeneity in BEV eVMT, we extract BEV sedan listings and estimate the following model with additional controls for the annual mileage:

$$mileage = \beta_0 + \beta_1 age + \beta_2 age^2 + \sigma age\_interaction + \beta controls + \epsilon_i$$

In this model, we created two sets of dummy variables: tesla and climate zone. tesla is an indicator of whether a listing is a Tesla brand or not. This is important because Tesla BEVs have substantially greater driving ranges than many other BEV models available, and because Tesla has established its own private charging network. Climate zone is a set of dummy variables that indicate in which climate zone the listing is located in as determined by the IECC definition, which categorizes U.S. states into 7 different climate zones based on temperature, humidity, rainfall, and other weather factors [24]. Since BEV range performance declines in colder weather [25][26][27], it is hypothesized that BEVs in colder climates may have less mileage than those in warmer climates, all other factors equal. Table 4 lists the regression results from the model above. From Model 3 to Model 6, we are adding controls and interaction terms step-by-step. By interacting with age (measured in years), we could separately estimate those variables' impact on annual eVMT. Total effect will be the sum of interaction term and age. In the final model, Model 6, we added control variable for states which we left out of the regression table.

	Model 3	Model 4	Model 5	Model 6 - control for states
(Intercept)	-2.817598***	-9.176684***	-4.167878***	-5.009655*
	(0.140873)	(0.373754)	(0.766399)	(2.374429)
age_years	8.268763***	10.366039***	9.118704***	8.982419***
	(0.060244)	(0.127891)	(0.206060)	(0.206389)
tesla	-0.413125**	7.583573***	16.545189***	16.410791***
	(0.140163)	(0.639190)	(1.429153)	(1.430136)
age_years^2	-0.206722***	-0.378572***	-0.358021***	-0.343957***
	(0.006087)	(0.008681)	(0.009109)	(0.009211)
age_years:tesla	2.072940***	1.782979***	-0.008184	0.114926
	(0.034010)	(0.133885)	(0.265085)	(0.265285)
range		0.040486***	-0.031800**	-0.033362***
		(0.002197)	(0.009718)	(0.009725)
age_years:range		-0.005645***	0.011139***	0.010586***
		(0.000625)	(0.002361)	(0.002359)
tesla:range		-0.052910***	-0.092289***	-0.091996***
		(0.003070)	(0.006326)	(0.006329)
age_years:tesla:range		0.003335***	0.011283***	0.010442***
		(0.000759)	(0.001271)	(0.001274)
range^2			0.000220***	0.000222***
			(0.000029)	(0.000029)
age_years:range^2			-0.000051***	-0.000047***
			(0.000007)	(0.000007)
Num. obs.	272126	184092	184092	184092
R^2 (full model)	0.443295	0.457707	0.457888	0.459742
R^2 (proj model)				
Adj. R^2 (full model)	0.443287	0.457684	0.457858	0.459557
Adj. R^2 (proj model)				

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 4: Bev model result. Estimators are significant at 1% level.

Besides the aging effect, is the analysis showed that range also a major factor affecting eVMT. On average, 100 more miles of driving range is associated with 1,000 more annual eVMT. However, the negative sign on the *age*range^2* estimator suggests that this range effect declines with increasing range, suggesting that it is stronger for lower-range BEVs than higher-range BEVs. Another take away from this model is that in Model 6, which is the regression analysis that includes all the regressors listed in Table 4, Tesla does not have a significant impact on annual eVMT by itself anymore. The coefficient for *age*tesla*range* suggests that their uniquely high eVMT is associated to their range. A 300-mile range Tesla will have 1,500 more annual eVMT compared to other models that with same range. Given that other BEV models do not have such long range or an equivalently reliable charging network, the results from the models without the *range^2* term may suggest that the Tesla effect is more significant than it is in reality.

Finally, we also see that Tesla BEVs are driven much more closely to CVs than non-Tesla BEVs. On average, a Tesla BEV is driven close to 10,500 miles per year compared to just average 6,926 miles for non-Teslas. If range effects are included, Teslas are expected to accumulate more than 10,000 miles annually, which is close to the CV VMT in Figure 3. Because the BEV market has a limited number of models available, most high-range BEVs are Teslas. In addition, Tesla's charging infrastructure is much more widespread and reliable than the charging networks available to other BEVs. Both of these factors are influential in Tesla BEVs being driven so much more than non-Teslas. This result suggests that as PEVs become available with longer ranges and more reliable charging networks, people will be more likely to drive them more closely to a CV.

As PEV driving behaviors approach those of CVs, it makes sense that the average consumer will be more inclined to adopt an electric vehicle. While adoption rates increase, the PEV effect on the energy load will become more significant. In order to minimize the impact of PEVs on the grid, the mileage information that was found with this work should be combined with PEV driver charging behavior to not only understand the total kWh that will be needed to power PEVs each year but what time of day that energy is needed. An EPRI study on the driving and charging behaviors in the Salt River Project (SRP) utility jurisdiction found that the Teslas they tracked from July 2017 to October 2018 used approximately 2,380 to 7,159 kWh per year

[29]. As a result, managing charging load will be essential. Fortunately, early consumers seem to be responsive to TOU rates [29], which may be very helpful in managing load as more PEVs, both new and used, enter the market.

4 Conclusion

Higher PEV adoption, whether through new or used PEVs, will have a significant effect on the market. Tracking how vehicle miles traveled differ between vehicle powertrains and model will be essential in identifying whether or not the general public is treating PEVs as a suitable substitute to CVs. While we have seen that there is a marked difference between the way BEVs and CVs are driven, there are a lot of insights to be learned from HEVs, PHEVs, and the other regressors considered in the model. Factors like whether or not a car is a Tesla has a significant impact of their driving behavior. As the PEV market develops and includes more car types with long ranges, and more accessible and reliable public chargers, the difference between PEV and CV driving behaviors will most likely become less apparent. Understanding adoption trends and distinct driver behaviors will be crucial to utility members and policy makers. They will need that information to ensure that the additional load created by PEVs can be covered adequately.

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2 Presenter Biography

Allan Zhao is an Engineer/Scientist with Electric Power Research Institute (EPRI). At EPRI, Allan engages with policy and data analysis for the Electric Transportation team. Prior to his role at EPRI, Allan has worked with electric vehicle policy and research at the California Air Resources Board (CARB), United States Congress, and various other public offices. These roles complement his education from Stanford University, where he earned both his B.A. in Political Science and M.S. in Sustainability Science and Practice.