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Quantifying electric vehicle mileage in the United States

Examining odometer readings of used vehicles from 2016 to 2022, this study reveals that battery electric vehicles (BEVs) are driven less annually than conventional gasoline vehicles (CVs). Tesla BEVs accumulate more miles than their non-Tesla counterparts, and larger BEV ranges correlate with higher annual mileage, though with diminishing returns with increased driving ranges. With current BEV usage lagging behind CVs, infrastructural upgrades and longer BEV ranges may be required for parity in usage patterns.

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Highlights

BEVs accumulate fewer annual miles than CVs: 7,165 versus 11,642 (cars)

Tesla BEVs have higher annual miles than non-Teslas: 8,786 versus 6,235 (cars)

Larger range BEVs are driven more, though diminishing returns are noticed

CV mileage shows higher sensitivity to cost increases than BEV mileage

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Quantifying electric vehicle mileage in the United States

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SUMMARY

We deliver comprehensive, high-resolution estimates of annual vehicle miles traveled (VMT) in the United States for battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), hybrid electric vehicles (HEVs), and conventional gasoline vehicles (CVs) using odometer readings from 12.5 million used cars and 11.4 million used sport utility vehicles (SUVs) listed between 2016 and 2022. Although CVs, HEVs, and PHEVs are driven similarly, BEV cars average 4,477 fewer miles annually. Teslas are driven more than other BEVs, yet still less than CVs. Similar differences in VMT across powertrains exist for SUVs, though SUVs are driven more than cars in all powertrains. Driving range has a non-linear relationship with VMT for BEV cars: every 10 additional miles of range equates to 631 additional annual miles for low-range BEVs (<100 miles of range) but only 85 annual miles for high-range BEVs (>200 miles of range). BEV cars also show less sensitivity in annual VMT to operating cost changes compared with CVs. Results provide an important context for modelers anticipating increased electricity consumption from PEV adoption.

CONTEXT & SCALE

Mass adoption of plug-in electric vehicles (PEVs) is a critical component of plans to decarbonize the US energy system. Understanding current PEV usage helps inform future planning. Analyzing the odometer readings from millions of used cars and SUVs listed between 2016 and 2022 reveals that battery electric vehicles (BEVs) have accumulated fewer annual miles than conventional gasoline vehicles (CVs): 7,165 compared with 11,642 for cars, and 10,184 compared with 12,979 for SUVs. Tesla BEVs have accumulated more annual miles than non-Teslas: 8,786 compared with 6,235 for cars and 8,970 compared with 8,553 for SUVs. BEVs with larger ranges were driven more, but increasing range has diminishing returns in terms of higher annual mileage. BEV sensitivity to operating costs was also less than other powertrains: for every 1 cent/mile cost increase, CV cars were associated with 140 fewer annual miles compared with only 59 for BEVs. These results suggest that assuming equal usage between BEVs and CVs is, at least in the short term, an optimistic assumption. Although future BEV usage might mirror that of CVs with more charging infrastructure, longer-range BEVs, or higher gas prices, current BEV usage patterns are well below those of CVs.

INTRODUCTION

Mass adoption of plug-in electric vehicles (PEVs) is a critical component of plans to decarbonize the United States (US) energy system.[1,2] As a result, PEVs are anticipated to be one of the largest sources of new electricity demand in coming decades.[3] Because the scale of this electricity consumption hinges on PEV utilization patterns, precise estimates of PEV vehicle miles traveled (VMT) are crucial for policymakers and modelers preparing for a world with more PEVs.

Many studies that attempt to quantify the electricity demand from PEV usage (and the associated environmental impacts) assume equal VMT between PEVs and gasoline-powered conventional gasoline vehicles (CVs),[4–9] but this assumption could lead to unrealistic conclusions if actual VMT differs. Likewise, the environmental benefits from PEVs scale with usage,[10] and those benefits may be over-estimated if true usage is lower than assumed. Accurate VMT estimates may also become important for future government budget planning as scholars are increasingly calling to replace the gasoline tax with a vehicle mileage tax.[11–13] Finally, VMT is informative for assessing how well PEVs are performing as a direct substitute for CVs,[14] which has important implications for their overall adoption rate.

Despite the significance of such an important metric, prior published estimates of PEV VMT have conflicting results, concluding that battery electric vehicle (BEV) cars are driven as little as 6,300 annual miles[15] and as much as 12,522 annual miles.[16] Table 1 summarizes prior studies that have attempted to quantify BEV VMT. One

Table 1. Summary of estimated BEV mileage from previous studies

Study	Estimated annual VMT	Sample location	Sample size[a]	Data year(s)	Data source
Davis[15]	6,300	US	436	2017	NHTS[b]
Burlig et al.[22]	6,700	California	57,290	2014–2017	household electricity meter readings
Rush et al.[23]	8,838	US	unknown	2013–2021	Edmunds vehicle listings
Jia and Chen[24]	10,000	California	184	2019	2019 California Vehicle Survey
Chakraborty et al.[25]	11,250	California	2,373	2015–2019	California Vehicle Survey
Tal et al.[16]	12,522	California	100	2015–2018	on-board vehicle sensors
This study (2023)	7,165 (cars) 10,587 (SUVs)	US	175,773 (cars) 12,623 (SUVs)	2016–2022	used vehicle listings

[a]BEV cars only.
[b]National Household Travel Survey.[17]

data source used in prior studies is the National Household Travel Survey (NHTS), a relatively large-scale and nationally representative dataset collected by the Federal Highway Administration.[17] Analyses of the latest NHTS suggest that BEVs are driven approximately 66% as much as CVs on an annual basis.[15,18] 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 lower BEV mileage estimates from these studies may not be representative of how BEVs are being driven today, both because earlier BEV generations had significantly shorter driving ranges than today's BEVs[19] and because the earlier generation of BEV owners may have substituted some trips with other household vehicles.[19–21]

Another approach to estimating VMT is to extrapolate it from related data sources, such as electricity meter readings. Burlig et al.[22] collected home meter readings from 2014 to 2017 in California and combined them with vehicle registration data to create a sample of 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 households purchased a BEV and then extrapolated the results into the expected miles driven. Their results suggest BEVs were driven 6,700 miles on average each year. Although this estimate benefits from a large sample size, the results rely on assumptions about where drivers charged their vehicles and may underestimate true VMT if more charging was done outside of the home.[22,26] These data also only represent BEVs in California operating between 2014 and 2017, which are neither nationally representative nor up to date, given the advances in BEV technology and landscape since then.

To overcome the limitations of indirectly measured VMT, some researchers have used on-board vehicle sensors to directly observe real-world BEV usage patterns.[20,27–30] In the detailed analysis by Tal et al.[16] on the driving patterns of BEV and plug-in hybrid electric vehicle (PHEV) owners in California, data loggers were installed on PEVs in 264 households in California. After 1 year of observation, the average annual VMT for BEVs was 12,522 miles—nearly double the estimate from Burlig et al.[22] 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 trips with other household CVs.[16] Other similar studies that use sensors to directly measure VMT also found relatively higher BEV VMT than the studies that indirectly measured VMT.[20,24,28] Nonetheless, despite the high data quality of these studies, the samples obtained are relatively small (100–200 participants) and limited to California households. These studies may also suffer from selection effects if participants were unusually high-mileage drivers.

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In this study, we attempt to overcome these prior limitations by using a direct measurement of mileage (odometer readings) collected from a large, nationally representative dataset of used vehicle listings in the US. Used vehicle listings have been used before to assess annual VMT; a 2022 report by Argonne National Laboratory estimated annual BEV cars drove 8,838 miles per year on average, although the data used were median mileage estimates from Edmunds.com rather than raw odometer readings.[23] The listing data used in this study are licensed from marketcheck.com, a market research firm that collects vehicle listing data from individual dealership websites on a daily basis. These data include the listing date, dealership address, and data about the vehicle, including the make, model, trim, model year, listing price, powertrain, and (most crucially) the odometer reading. Additional data on BEV and PHEV electric driving ranges as well as estimated operating costs for all vehicles were added to control these important features. BEV and PHEV range as well as all vehicle efficiencies (miles per gallon for gasoline-powered vehicles, and kWh per 100 miles for electricity-powered vehicles) are primarily from fueleconomy.gov,[31] with a small number of missing values added from carsheet.io.[32] Monthly gasoline prices[33] and annual average electricity prices[34] in different states are from the US Energy Information Administration (EIA). These prices were combined with vehicle efficiencies to compute an estimated average operating cost (in cents per mile) over the vehicle's life up until being listed in the used market. For PHEVs, a utilization factor (0–1) from fueleconomy.gov was used to compute the gas and electric portions of operating costs (a more detailed description of the operating cost calculation is included in the experimental procedures).

We focus on car and sport utility vehicle (SUV) listings since few BEV pickups were listed in the time period captured in the dataset (January 2016 to February 2022). In addition, we censored the data to only include vehicles with ages between 2 and 9 years as few BEV listings were present in the dataset outside of this period and because mileage may accumulate differently for used vehicles listed before 2 years of age (e.g., vehicles listed quickly after being bought new may need repairs and thus may have fewer miles than otherwise is typical). We also only include vehicle models that comprised at least 1% of the listings within each powertrain as a practical compromise between including a representative sample of vehicles while remaining computationally reasonable as the majority of the listings are composed of a smaller number of models and a large number of models have very few listings (e.g., exotic cars). The final dataset includes 12,511,667 unique used car listings and 11,391,430 unique used SUV listings from 66,641 dealerships. Table 2 summarizes the dataset by powertrain and vehicle type (car or SUV), with Tesla and non-Tesla BEVs separated, given Tesla's unique prominence and features in the BEV market, including higher-range vehicles and a private fast-charging network. Extended data Tables S1 and S2 summarize each car and SUV model included in our analyses, respectively.

RESULTS

Using odometer readings to model vehicle mileage

Figure 1 compares the rate of mileage accumulation of CV cars with that of hybrid electric vehicle (HEV), PHEV, and BEV cars, where the median (solid lines) and interquartile ranges (bands) of odometer readings were computed for all listings in each month of age. Although HEVs and PHEVs accumulate miles at a relatively similar slope to CVs, BEVs appear to be driven significantly less, a finding consistent with several previous studies.[15,22,24] Extended data Figure S1 show the separate curves for Tesla and non-Tesla BEVs.

Table 2. Summary statistics of used car and SUV listings

	Conventional	Hybrid	PHEV	BEV (non-Tesla)	BEV (Tesla)
Cars					
Vehicle listings	11,643,966	562,747	128,850	118,911	57,193
Vehicle models	25	15	7	10	2
Miles (1,000)					
Mean	51	54	43	27	36
SD	31	33	25	15	21
Age (years)					
Mean	4.3	4.5	4.1	4.1	4.2
SD	1.7	1.7	1.4	1.4	1.5
Price ($USD)					
Mean	16,205	15,943	19,311	15,025	50,181
SD	6,814	4,932	12,820	9,287	12,380
Electric range (miles)					
Mean	–	–	32	104	251
SD	–	–	14	49	50
Min	–	–	11	58	139
Max	–	–	53	259	402
SUVs					
Vehicle listings	11,333,997	44,190	0	1,732	11,511
Vehicle models	35	8	–	1	2
Miles (1,000)					
Mean	51	46	–	13	33
SD	31	28	–	9	18
Age (years)					
Mean	4.2	4.1	–	2.7	3.8
SD	1.6	1.6	–	0.4	1
Price ($USD)					
Mean	21,413	29,049	–	61,779	71,613
SD	7,788	10,248	–	6,576	14,135
Electric range (miles)					
Mean	–	–	–	204	266
SD	–	–	–	0	31
Min	–	–	–	204	200
Max	–	–	–	204	371

To quantify this difference, we estimate a linear model of odometer readings versus age (in years) interacted with the vehicle powertrain to identify differences between the annual VMT slopes by powertrain. Table 3 shows the estimation results. Models 1a and 2a pool all BEVs together, and models 1b and 2b separate the BEVs into Tesla and non-Tesla, under the expectation that Teslas would be driven differently, given their higher driving ranges and well-established charging infrastructure. For cars, CV VMT increases on average by 11,642 miles per year. Although HEV cars are driven slightly more at 11,941 miles per year and PHEVs slightly less at 11,113 miles per year, BEVs are driven substantially less at just 7,165 miles per year (approximately 39% less than CVs). Tesla BEV cars are driven more at 8,786 annual miles compared with just 6,235 annual miles for non-Teslas, but still approximately 25% less than CVs annually. Similar differences in VMT across powertrains exist for SUVs, although SUVs are driven more than cars in all powertrains with annual mileages of 12,979 for CVs, 12,126 for HEVs, 8,970 for Tesla BEVs, and 8,553 for non-Tesla BEVs.

Figure 2 shows the odometer readings versus age from every listing with the resulting slope from models 1b and 2b overlaid. The figure illustrates that in addition to

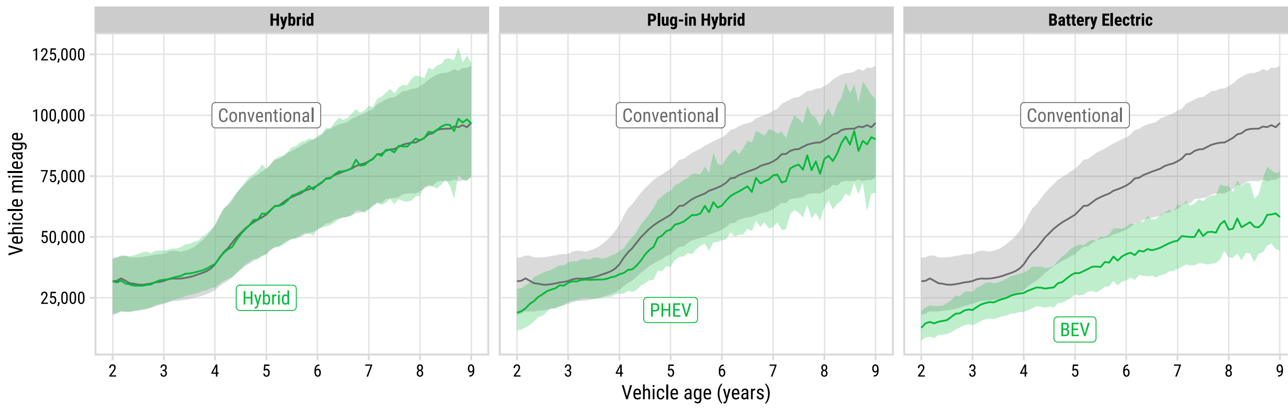

Figure 1. Comparison of the median and interquartile ranges of car odometer readings by powertrain and age

The solid line shows the median mileage and the bands reflect the 25th and 75th percentiles. The same curve for CVs (in gray) is shown for comparison in each sub-figure.

having a lower annual VMT, BEVs also appear to have less variance in mileage accumulation compared with CVs and HEVs, with root mean square error measures of 23.8 for CV cars and 14.7 for BEV cars on separate models estimated on each powertrain. It is clear that BEVs are not yet being used as substitutes for many CV trips and, in particular, high-mileage drivers. Nonetheless, there are observations of higher-mileage BEV users in the dataset. A best-fit line using only the top 10% of the highest mileage BEV cars in each month of age (17,611 BEVs) has a slope of 12,135 annual miles—higher than the average slope for all CV users. Across the sample of CVs, 46% of the observations (5,365,367 CVs) have odometer readings at or below this annual VMT.

To further investigate relationships between annual VMT and other features, we estimate four additional models (one for each powertrain) for cars and SUVs, shown in Tables 4 and 5. To understand the relationship between BEV driving range and annual VMT, we divide the BEV cars into three groups based on natural clusters in the data: low-range (<100 miles), mid-range (between 100 and 200 miles), and high-range (>200 miles). For BEV SUVs, we ignore this clustering as the sample contains only three unique vehicle models (the Tesla models X and Y, and the Audi e-tron). Results suggest that additional BEV driving range matters much more for lower-range cars compared with higher-range cars: every 10 additional miles of range equates to 631 additional annual miles for low-range BEVs, 412 additional annual miles for mid-range BEVs, and only 85 annual miles for high-range BEVs. This suggests that there may be limits to achieving higher annual VMT from increasing range alone. The Tesla coefficients in model 3a are also noteworthy as they are the highest among the BEV car models. Even after controlling for Tesla's higher driving ranges, model 3a suggests that Teslas are driven further at 1,056 and 538 more annual miles relative to a Nissan Leaf for the model 3 and model S, respectively. Although similarly large differences are also observed across models in other powertrains, Teslas are the only BEVs in our sample that have access to a well-established fast-charging network across the US, enabling Tesla drivers to travel longer distances and encouraging long-distance drivers to purchase Tesla BEVs over other alternatives.

Operating cost is another important feature explored in the models in Table 4. We find that for cars, BEV VMT is less sensitive to changes in operating cost compared with other powertrains: for every 1 cent per mile increase in operating costs, CVs are

Table 3. Model coefficients from linear models of vehicle mileage versus age with powertrain interactions

	Cars		SUVs	
	Model 1a	Model 1b	Model 2a	Model 2b
Intercepts				
(Intercept)	0.716*** (0.019)	0.716*** (0.019)	−4.104*** (0.018)	−4.104*** (0.018)
Powertrain_hybrid	−0.124 (0.093)	−0.124 (0.093)	0.634* (0.295)	0.634* (0.295)
Powertrain_PHEV	−4.005*** (0.203)	−4.005*** (0.203)	–	–
Powertrain_BEV	−0.302 (0.177)	–	−3.081*** (0.710)	–
Powertrain_BEV_non_Tesla	–	0.777*** (0.219)	–	−6.371 (3.657)
Powertrain_BEV_Tesla	–	−1.291*** (0.299)	–	2.722*** (0.800)
Age_years	11.642*** (0.004)	11.642*** (0.004)	12.979*** (0.004)	12.979*** (0.004)
Interactions with age_years				
Powertrain_hybrid	0.299*** (0.019)	0.299*** (0.019)	−0.853*** (0.068)	−0.853*** (0.068)
Powertrain_PHEV	−0.529*** (0.046)	−0.529*** (0.046)	–	–
Powertrain_BEV	−4.477*** (0.040)	–	−2.795*** (0.186)	–
Powertrain_BEV_non_Tesla	–	−5.407*** (0.050)	–	−4.425*** (1.344)
Powertrain_BEV_Tesla	–	−2.856*** (0.067)	–	−4.009*** (0.202)
Number of observations	12,511,667	12,511,667	11,391,430	11,391,430
R^2	0.405	0.406	0.480	0.480

Mileage is in units of 1,000 miles. *** $p < 0.001$, **$p < 0.01$, *$p < 0.05$. Standard errors are presented in parentheses.

driven 140 fewer miles, but BEVs, just 59 fewer miles per year. This is an intuitive finding consistent with prior research that has found drivers have higher elasticity to gasoline prices than to electricity prices.[35,36] Gasoline prices are also heavily advertised on roads, and drivers interact with them at each refueling, increasing their salience. Electricity is observed less frequently (usually via a monthly utility bill), and the total electricity cost is not itemized, making vehicle charging costs less obvious. Finally, since BEVs are much more efficient than other powertrains, drivers may be less sensitive to increases in electricity prices. Figure 3 shows the distribution of operating costs across all cars and SUVs in our sample. For both cars and SUVs, the highest operating cost BEV is near the lower bound of the interquartile range of operating costs for the CVs.

Although a positive sign on the operating cost term for PHEV cars is unexpected, there are several reasons that could explain this outcome. First, our estimate of operating costs for PHEVs may be inconsistent with true costs for PHEV owners. This could be due to the assumptions used to compute operating costs, which are aligned with the calculations made by the Department of Energy's fueleconomy.gov[31] or due to a mismatch between these assumptions and true user behavior. Prior research has found that shorter-range PHEVs tend to be charged less frequently and as much as one-third of the PHEV owners may rarely charge their vehicle.[37] If the estimated operating costs for certain PHEVs are misaligned with their true costs while others are aligned, then estimated outcomes could vary substantially. Another possible explanation is the potential for intra-household substitution for multi-vehicle households, that is, households that own a PHEV and CV may tend to drive the PHEV more often than the CV if gasoline prices are higher, leading to a positive relationship between mileage and operating cost. For these reasons, we caution drawing conclusions from the operating cost coefficients for PHEVs in this analysis.

Exploring low BEV mileage

The low BEV mileage observed in the listing data could be the result of a number of factors. Although fully explaining the underlying causes is not possible with the

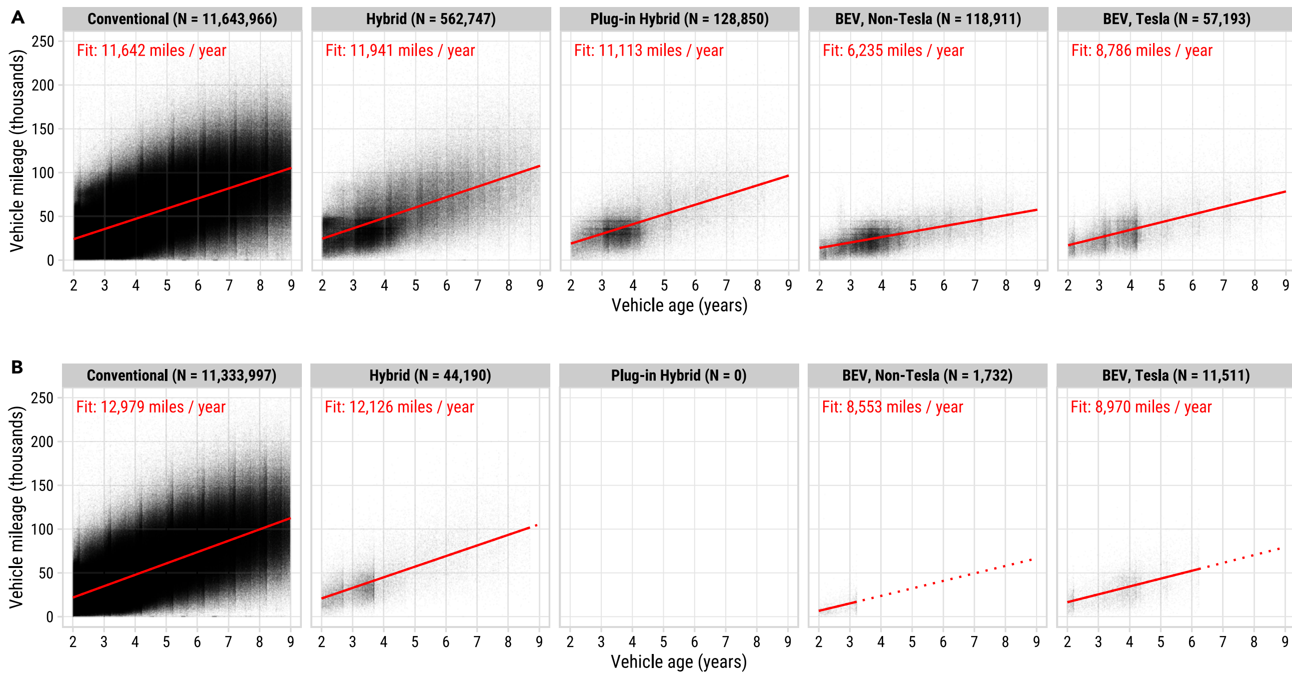

Figure 2. Scatterplot of vehicle odometer readings (thousands of miles) versus age (years) by vehicle powertrain
The red lines are the best-fit linear models for each powertrain (model 1b for cars and model 2b for SUVs), and the dotted lines are extrapolations beyond the range of observed data.

listings data alone, we conduct additional analyses to provide some suggestive evidence and greater context for future studies to build upon.

Time effects

The first additional analysis is to examine whether BEV mileage is changing over time. The availability of longer-range BEV models and the construction of charging infrastructure have both increased substantially during the period our data captures; as a result, it is reasonable to expect that more recent BEV models may have higher VMT than earlier models. Unfortunately, this is difficult to measure using vehicle listings data as the number of observations (and the majority of the variability in vehicle age) is concentrated in older rather than newer model year vehicles. This is a natural outcome from the fact that older model years have had more time to show up at used vehicle dealerships and thus appear more often in the database. For example, the oldest that a 2021 model year car in our dataset could be is only 1 year old (if listed in 2022), but a 2012 model year car could be anywhere from 4 to 9 years old (listed anytime between 2016 and 2022). As a result, fitting a linear model for newer model years may be less reliable as the slope will be determined by a smaller number of observations and from a narrower range of vehicle age. Furthermore, since BEV range is correlated with vehicle model year (newer models have higher driving ranges), it is difficult to separately identify range and age effects.

With these limitations in mind, we attempt to measure time effects by estimating additional models on BEV cars, presented in extended data Table S3. Model 5a is the same as model 3a in Table 4 and is listed for comparison purposes. Model 5b includes a squared term on age to allow for the possibility of a non-linear mileage accumulation over time. Model 5c includes the model year of each vehicle as dummy variables to account for potential VMT changes with newer models, and model 5d includes these model year variables and the squared age term.

Table 4. Coefficients from linear models estimated on each separate powertrain with state and model year fixed effects (cars only)

	Model 3a	Model 3b	Model 3c	Model 3d
Powertrain	BEV	PHEV	Hybrid	Conventional
Age_years	5.835*** (0.422)	12.902*** (0.399)	13.372*** (0.356)	11.518*** (0.033)
Operating cost and range interactions with Age_years				
Cents_per_mile	− 0.059** (0.020)	0.522*** (0.039)	0.071* (0.030)	− 0.140*** (0.002)
Range	0.009*** (0.001)	− 0.182*** (0.011)	–	–
Range * range_low (<100 miles)	0.055*** (0.010)	–	–	–
Range * range_mid (100–200 miles)	0.033*** (0.009)	–	–	–
Select model interactions with Age_years				
Reference level:	Nissan Leaf	Toyota Prius Prime	Honda Accord	BMW 3 Series
Bolt EV	− 5.672*** (0.293)	–	–	–
Model 3	1.056*** (0.292)	–	–	–
Model S	0.538* (0.244)	–	–	–
i8	–	− 9.179*** (0.338)	–	–
Volt	–	2.108*** (0.288)	–	–
Civic	–	–	1.966*** (0.393)	1.723*** (0.026)
Fusion hybrid	–	–	− 3.510*** (0.334)	–
Corolla	–	–	–	0.359*** (0.028)
Mustang	–	–	–	− 1.418*** (0.031)
Outback	–	–	–	3.178*** (0.031)
Number of observations	175,773	128,850	528,674	11,643,966
R^2	0.412	0.460	0.394	0.449

Age is interacted with operating costs (in cents per mile), vehicle model, and electric driving range for BEVs and PHEVs. For conciseness, intercept terms are omitted and only vehicle model interactions with the highest and lowest estimated effects are included. Mileage is in units of 1,000 miles. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Standard errors are presented in parentheses.

All of the models in extended data Table S3 have similar vehicle model fixed effects (e.g., both Tesla vehicle models have positive VMT effects in all models). The negative sign on the squared age effect in models 5b and 5d suggests that older BEVs are accumulating mileage slower than newer ones, although the effect size is relatively small. When model year effects are added (models 5c and 5d), the range effect increases and the differences by range category lose significance, which is unsurprising as newer model years have higher driving ranges and differences are being captured by the model year effects. Models 5c and 5d provide little evidence that annual mileage is increasing in model years 2013–2018; however, both models show a large, positive effect in model year 2019. Although this does suggest that we may be entering a period where BEVs are driven more, it is important to keep in mind the limited amount of data available (and more importantly the limited variation in age) for this model year. The model year 2019 has just 10,484 listings, and the maximum age is 3.2 years old; as a result, the higher mileage for 2019 model years could be an artifact of those vehicles all being younger. Further investigating this trend will be a primary motivation to replicate this study when newer data become available as newer BEVs age and enter the resale market.

Multi-vehicle households

Another plausible explanation for low BEV VMT is if BEVs are purchased as secondary rather than primary household cars. Unfortunately, the listings data do not reveal any information about the buyers of the listed vehicles, and therefore, we are unable to include household demographics in our analyses. However, the 2017 NHTS data do include household demographics, and although the survey contains few BEV observations, it does include a large sample of CVs, which can be used to investigate the effects of household characteristics on CV mileage. Although households with

Table 5. Coefficients from linear models estimated on each separate powertrain with state and model year fixed effects (SUVs only)

	Model 4a	Model 4b	Model 4c
Powertrain:	BEV	Hybrid	Conventional
Age_years	12.104*** (1.885)	12.867*** (0.979)	16.644*** (0.049)
Operating cost and range interactions with Age_years			
Cents_per_mile	− 0.343*** (0.095)	− 0.257*** (0.072)	− 0.279*** (0.003)
Range	−0.005 (0.008)	–	–
Select model interactions with Age_years			
Reference level:	Audi e-tron	Porsche Cayenne	Toyota 4runner
Model X	0.477 (0.988)	–	–
Model Y	4.926 (9.001)	–	–
Escape	–	− 7.588*** (0.651)	− 1.188*** (0.030)
Highlander	–	2.705*** (0.399)	− 0.328*** (0.033)
RAV4	–	4.450 (2.447)	1.847*** (0.146)
Expedition	–	–	2.096*** (0.058)
Wrangler	–	–	− 3.475*** (0.039)
Number of observations	13,243	44,190	11,333,997
R^2	0.376	0.492	0.519

Age is interacted with operating costs (in cents per mile), vehicle model, and electric driving range for BEVs. No PHEVs observations were available. For conciseness, intercept terms are omitted and only vehicle model interactions with the highest and lowest estimated effects are included. Mileage is in units of 1,000 miles. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Standard errors are presented in parentheses.

BEVs may have different usage patterns, understanding differences in the usage of primary versus secondary vehicles in households with multiple CVs is still informative as a status quo for vehicle usage in multi-vehicle households.

Results from additional models examining household characteristics in the NHTS data are presented in extended data Table S4. Models 6a and 6c use CV cars, and model 6b uses hybrid cars. Although the NHTS data do not have a variable for distinguishing which vehicle is used as the primary vehicle, we use odometer readings as a proxy, where we define any vehicle as "secondary" if it has fewer miles than the vehicle with the highest odometer reading in the household. In model 6c, we loosen this definition to any vehicle that has less miles than that of the top two vehicles with the highest odometer readings in the household. We interact this variable for whether a vehicle is primary or secondary in a household with the vehicle age to assess differences in annual mileage accumulation between the vehicle types. To control for heterogeneity in driving demands, we also interact vehicle age with household size as dummy variables.

As expected, the model coefficients suggest that secondary vehicles are not driven as much as primary vehicles and that larger households have higher annual mileage than smaller households, all else being equal. Secondary CVs accumulate 1,063 fewer annual miles than primary CVs according to model 6a. The gap is larger (2,169 annual miles) for households with a hybrid as the primary vehicle (model 6b). Results are similar when a more flexible definition of secondary is used (model 6c). Although the gap in secondary vehicle mileage accumulation is substantial, it is still a smaller gap than that between CVs and BEVs in the listings data (4,492 on average across all BEV cars). This suggests that being used as a secondary vehicle may not fully explain the lower BEV mileage observed in the listings data, although it very well could play a considerable role. This analysis also motivates

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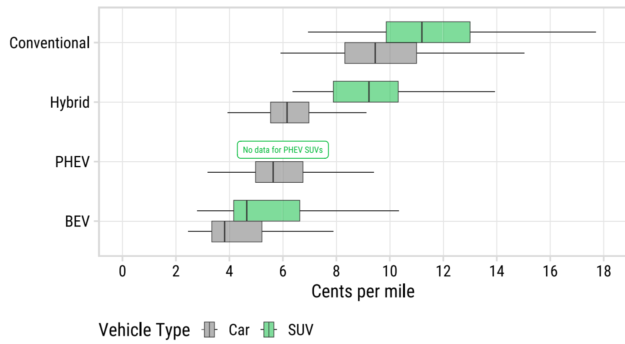

Figure 3. Distribution of operating costs across cars and SUVs in sample by powertrain
The boxes represent the values between the first and third quartile, and the whiskers represent 1.5 times the interquartile range beyond the first and third quartile.

the hypothesis that BEVs will be driven more in households that only own a BEV and no other vehicle.

DISCUSSION

Our finding that BEVs have not accumulated miles as quickly as vehicles with other powertrains is consistent with several prior studies. Our estimate of 7,165 annual miles on average is higher than the NHTS survey results from Davis[15] and the electricity usage results from Burlig et al.,[22] which underestimate our results by 865 and 465 annual miles, respectively, and lower than the estimate of 8,838 annual miles from Rush et al.,[23] which overestimates our results by 1,673 annual miles. The general alignment with the results from Burlig et al.[22] supports the method of using electricity consumption as a proxy for mileage, which may be able to provide more up-to-date mileage estimates for newer BEVs compared with using used vehicle listings, which take time to appear on the market. Our results also suggest that the studies that have directly measured BEV usage with on-board sensors may have experienced selection effects or other factors that have led to the small samples of participants in those studies driving BEVs substantially more than the average from our sample.[16,24] Although this study is not immune from selection effects, the large sample size provides a more comprehensive estimate of historical BEV usage compared with prior studies.

Although assessing the underlying causes of lower BEV mileage is beyond the scope of this study, additional analyses on the potential effects of time and multi-vehicle households provide suggestive evidence and greater context for future studies to build upon and make causal explanations. Low BEV mileage could be the result of a number of factors. With limited BEV driving ranges and immature charging infrastructure, some BEV drivers may drive less due to ''range anxiety,'' which has been shown to affect driving patterns.[38–40] Likewise, BEVs may have been disproportionately purchased by drivers with lower annual VMT needs, inducing a selection effect that results in lower mileage accumulation in the aggregate. Finally, because the majority of early BEV adopters own more than one vehicle,[19–21] these owners may choose to drive their BEV less, substituting it with another household vehicle for some trips and resulting in overall lower VMT for the BEV. Evidence from the 2017 NHTS data supports the multi-vehicle household hypothesis for CVs and remains a plausible source of at least some of the lower BEV mileage observed. Finally, there is some evidence that the most recent BEV models from model year 2019 and on may be driven more than previous model years, although the limitations of the listings data available prevent a strong conclusion about this phenomenon. Regardless of the underlying causes of lower BEV mileage, the much wider variance in observed VMT for CVs relative to BEVs suggests that few BEVs are being used to replace higher-mileage CV trips and that BEVs have been used more consistently among current owners.

This study provides an important context for modelers estimating the impacts of BEV adoption and usage. Models that assume equal substitution between BEV and CV usage are implicitly assuming an optimistic scenario that is inconsistent with historical usage. Accounting for true BEV usage would lead to lower expected emissions reductions from BEVs relative to CVs and lower electricity demand from BEVs.[10] Although it is certainly possible that future BEVs may be driven similarly to CVs, such scenarios may require changes to the operating environment, such as increased charging infrastructure, longer-range BEV availability, and potentially higher gasoline prices.

Finally, our findings also contribute to prior research on relationships between range and PEV usage. Prior studies suggest that range is a major factor restricting BEV utilization.[16,39,41] Although we cannot make a causal link between lower range and lower annual mileage, we do observe a statistically significant relationship between range and annual VMT as well as evidence that this relationship may be non-linear. As prior studies have found, BEV buyers exhibit a non-linear preference toward BEV range where the willingness to pay for additional mileage declines with increasing range.[42] Our study also reveals a similar non-linear relationship where increasing driving range equates to an order of magnitude larger increase in annual VMT for lower-range compared with higher-range BEVs, suggesting that there may be a limit to how much increased range translates to increased VMT. Likewise, results on operating costs are also consistent with prior research on "rebound" effects where more efficient vehicles are driven further, at least partially replacing some of the emissions and fuel savings from their higher efficiencies.[43–46] We find that when increasing operating costs, less efficient vehicles are associated with a larger reduction in annual VMT compared with more efficient vehicles like HEVs and BEVs.

This study has several important limitations. First, because the odometer readings are taken from used vehicle listings, they do not reflect the VMT of vehicle owners who never sold their vehicles. So long as the difference in VMT across powertrains does not vary between used vehicles and vehicles that are never re-sold, then this feature of the data should not impact our conclusions. Nonetheless, a plausible mechanism that could lead to lower estimated BEV mileage (but perhaps not affect mature technologies like HEVs and CVs) is if many of the BEV adopters discovered it was a poor fit for their needs and ended up driving it less before selling it. Another considerable limitation is the lack of demographic and household information about previous vehicle owner(s). It is certainly possible that the early PEV adopters who originally purchased the PEVs in our sample could exhibit substantial demographic differences, such as age, income, and the number of vehicles owned, compared with the general CV driver population. Such differences could influence or explain the relative differences in vehicle usage found in this study, and further research is needed to assess this possibility. In addition, the linear models used in this study imply an assumption that miles accumulate evenly and that vehicles are driven equally over their lifetimes. Although we find this to be generally valid in aggregate measures over the age range used in this study (vehicles between 2 and 9 years old), we acknowledge that changes in lifestyle and vehicle condition could influence the usage of individual vehicles by their owners (which we cannot observe using listings data) as well as the decision to sell or buy individual vehicles, inducing a selection process that may match drivers of a certain behavior to particular vehicles or powertrains. Finally, due to the nature of the data, older model year vehicles in the database appear in larger numbers and across greater age ranges than newer model years, limiting the ability to assess time trends. This is a fundamental limitation of using used vehicle listings as a data source, and future studies that use the same approach will also be limited in their ability to understand the behaviors of more recent vehicles compared with older ones.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Further information and requests for resources and materials should be directed to and will be fulfilled by the lead contact, John Paul Helveston (jph@gwu.edu).

Materials availability

This study did not generate new unique materials.

Data and code availability

All of the code used to process the data, estimate models, and produce all analyses and figures are publicly available at https://doi.org/10.5281/zenodo.8371109. The vehicle listings data that support the findings of this study are available from marketcheck.com, but restrictions apply to the availability of these data, which were used under a license agreement for the current study and so are not publicly available. A sample of the data is included in the GitHub repository to aid in evaluating the calculations made in this study. The relevant variables in the full original database can be provided on an individual bases for review purposes only to reproduce the study results by contacting the lead contact. All other data used in the study on vehicle specifications and fuel prices are publicly available and also posted in the repository.

Data preparation

We use used vehicle listings provided by marketcheck.com as the primary source for odometer readings. The primary interest of this study was comparing CV and BEV mileage. Unfortunately, before 2020 there were few BEV SUVs available, and the majority of used BEV SUVs in the listings data are Tesla model X SUVs. No BEV pickup trucks were available in the database. As a result, our primary analysis is on cars, but we also include an analysis of the limited number of SUVs as well. We limit our dataset to vehicle ages between 2 and 9 as fewer BEV listings are available outside of this range (fewer vehicles are listed used within 2 years of being new, and few used BEVs are older than 9 years old as of February 2022). We also only include vehicle models that comprised at least 1% of the listings within each powertrain as a practical compromise between including a sample that represents typical common cars while remaining computationally reasonable. As shown in extended data Table S1, just 25 vehicle models comprise 59% of the CV listings; the remaining 41% is composed of 852 additional vehicle models. Including these vehicle models would require far more coefficients to estimate (which is computationally expensive), and a considerable number of these vehicles are exotic or luxury cars, which are less representative of the typical car market. Although this 1% rule resulted in the inclusion of only 59% of the CV listings (nearly 13 million listings), it resulted in the inclusion of the vast majority of the other powertrains since they have far fewer vehicle models (96.3% of the BEVs, 97.1% of the PHEVs, and 94.7% of the HEVs).

BEV and PHEV ranges as well as all vehicle efficiencies (miles per gallon for gasoline-powered vehicles, and kWh per 100 miles for electricity-powered vehicles) are primarily from fueleconomy.gov,[31] with a small number of missing values added from carsheet.io.[32] Monthly gasoline prices[33] and annual average electricity prices[34] in different states are from the EIA. These data were joined onto the listings data based on the year, make, model, and trim.

All data preparations and visualizations were conducted in the R programming language[47] using the tidyverse[48] and arrow[49] packages.

Operating costs

Operating costs are estimated based on vehicle efficiencies and fuel prices at the US state level. For gasoline and electricity prices, we compute the mean price over the age of the vehicle in the state it was listed in using monthly gasoline prices and annual electricity prices. Operating costs for CVs and HEVs are computed as $100 * p^{gas}/e^{gas}$, where p^{gas} is the mean gasoline price and e^{gas} is the vehicle fuel economy in miles per gallon. For BEVs, operating costs are computed as $p^{elec} * e^{elec}/100$, where p^{elec} is the mean electricity price and e^{elec} is the BEV efficiency in kWh per 100 miles. For PHEVs, a utilization factor (0–1) from fueleconomy.gov was used to compute the gas and electric portions of operating costs using the respective equations above for each portion. Since our dataset only provides the date and zip code of the vehicle listing, we use this information as the proxy to actual vehicle usage location and period.

Linear models

To quantify annual VMT for each powertrain, we first estimate a linear model of vehicle mileage versus age interacted with the vehicle powertrain to identify differences between the annual VMT slopes by powertrain (the models in Table 3). To estimate the model, we treat each listing as an independent observation in the following model:

$$m = \alpha + \beta a + \gamma \boldsymbol{p} a + \epsilon \qquad \text{(Equation 1)}$$

where m is mileage (odometer readings in thousands of miles), a is age (in years), $\boldsymbol{p}$ is a matrix of dummy-coded vehicle powertrain variables with the CV powertrain set as the reference level, and ϵ is the error term. The β coefficient determines the annual VMT for CV powertrains and the coefficients in $\boldsymbol{\gamma}$ determine the difference in annual VMT for each other powertrain (HEV, PHEV, and BEV). The only difference between models 1a and 1b (and likewise 2a and 2b) is that the BEV powertrain is separated into Tesla and non-Tesla.

To further explore the heterogeneity within BEVs and PHEVs, we estimate the following model (the models presented in Tables 4 and 5):

$$m = \alpha + \beta a + \delta a c + \mu a r \boldsymbol{d} + \rho a \boldsymbol{v} + \sigma \boldsymbol{s} + \epsilon \qquad \text{(Equation 2)}$$

where m is mileage, a is age, c is operating cost (in cents per mile), r is electric driving range (in miles), $\boldsymbol{d}$ is a matrix of dummy-coded variables determining the BEV range category (low is r<100, mid is 100<r<200, and high is the reference level at r> 200), $\boldsymbol{v}$ is a matrix of dummy-coded vehicle model variables, $\boldsymbol{s}$ is a matrix of dummy-coded US state variables, and ϵ is the error term. Note that the age term (a) is interacted with all variables except states (s), and the range term (r) only applies to BEVs and PHEVs (models 3a, 3b, 4a, and 4b). The $\boldsymbol{d}$ variables are only included in the BEV car regression (model 3a) as a simplified approach to allow for non-linear range effects. The decision to break BEV car ranges into three categories was made because (1) it facilitates ease of interpretation (the coefficients can be immediately understood), (2) there are three naturally occurring groups in BEV car range in the data (below 100 miles, between 100 and 200 miles, and above 200 miles).

For the NHTS model results in extended data Table S4, we estimate the following model on CV and HEV cars:

$$m = \alpha + \beta a + \delta ac + \mu ad + \rho a\mathbf{h} + \nu \mathbf{y} + \sigma \mathbf{s} + \epsilon \qquad \text{(Equation 3)}$$

where m is mileage, a is age, c is operating cost, d is a dummy-coded variable for whether a car is a secondary car, h is a matrix of dummy-coded variables representing household size, $\mathbf{y}$ is a matrix of dummy-coded variables representing the vehicle model year, and $\mathbf{s}$ is a matrix of dummy-coded US state variables. All models were estimated in the R programming language[47] using the fixest[50] package.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.joule.2023.09.015.

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AUTHOR CONTRIBUTIONS

Conceptualization, J.P.H. and L.Z.; methodology, L.Z., E.O., and J.P.H.; software, L.Z. and J.P.H.; validation, A.Y.; formal analysis, L.Z. and J.P.H.; investigation, L.Z., E.O., A.Y., and J.P.H.; data curation, J.P.H.; writing – original draft, L.Z.; writing – review & editing, E.O., A.Y., and J.P.H.; visualization, E.O. and J.P.H.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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