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 hybrids (PHEVs), hybrids (HEVs), and conventional vehicles (CVs) using odometer readings from 12.5 million used cars and 11.4 million used SUVs listed between 2016 and 2022. While 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 to CVs. Results provide an important context for modelers anticipating increased electricity consumption from PEV adoption.

Keywords: Electric Vehicles, Mileage, Behavior, Vehicle Miles Traveled (VMT), eVMT.

Introduction

Mass adoption of plug-in electric vehicles (PEVs) is a critical component of plans to decarbonize the United States (U.S.) energy system^{39,20}. As a result, PEVs are anticipated to be one of the largest sources of new electricity demand in coming decades⁴³. 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 vehicles (CVs)^{11,12,18,19,27,42}, but this assumption could lead to unrealistic conclusions if actual VMT differs. Likewise, the environmental benefits from PEVs scale with usage²¹, 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^{26,45,6}. Finally, VMT is informative for assessing how well PEVs are performing as a direct substitute for CVs⁴⁴, 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 miles⁴ and as much as 12,522 annual miles⁴¹. Table 1 summarizes prior studies that have attempted to quantify BEV VMT. One 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 Administration¹³. Analyses of the latest NHTS survey suggest that BEVs are driven approximately 66% as much as CVs on an annual basis^{4,25}. 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 BEVs⁵, and because the earlier generation of BEV owners may have substituted some trips with other household vehicles^{35,38,5}.

[Table 1 here]

Another approach to estimating VMT is to extrapolate it from related data sources, such as electricity meter readings.² 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. While 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^{34,2}. These data also only represent BEVs in California operating between 2014-2017, which is not 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 onboard vehicle sensors to directly observe real-world BEV usage patterns^{40,35,31,17,32}. In the detailed analysis by⁴¹ on the driving patterns of BEV and PHEV owners in California, data loggers were installed on PEVs in 264 households in California. After one year of observation, the average annual VMT for BEVs was 12,522 miles—nearly double the estimate from² 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 CVs⁴¹. Other similar studies that use sensors to directly measure VMT also found relatively higher BEV VMT than the studies that indirectly measured VMT^{22,35,31}. Nonetheless, despite the high data quality of these studies, the samples obtained are relatively small (100 to 200 participants) and limited to California households. These studies may also suffer from selection effects if participants were unusually high-mileage drivers.

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 data set of used vehicle listings in the U.S. 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, though the data used were median mileage estimates from Edmunds.com rather than raw odometer readings³⁷. 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. The data include the listing date, the 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 was added to control for 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.gov⁸, with a small amount of missing values added from carsheet.io³. Monthly gasoline prices¹⁰ and annual average electricity prices⁹ in different states are from the U.S. 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 to 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 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 to 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 two 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 comprised of a smaller 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 out 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.

[Table 2 here]

Results

Using odometer readings to model vehicle mileage

Figure 1 compares the rate of mileage accumulation of CV cars with that of 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. While 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^{4,2,22}. Extended Data Figure S1 shows the separate curves for Tesla and Non-Tesla BEVs.

[Figure 1 here]

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. While 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 to 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, though 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.

[Table 3 here]

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 having a lower annual VMT, BEVs also appear to have less variance in mileage accumulation compared to CVs and HEVs, with 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 observations (5,365,367 CVs) have odometer readings at or below this annual VMT.

[Figure 2 here]

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 (< 100miles), mid-range (between 100 - 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 Model X and Y, and the Audi e-tron). Results suggest that additional BEV driving range matters much more for lower-range cars compared to 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 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 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. While 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 U.S., enabling Tesla drivers to travel longer distances and encouraging long-distance drivers to purchase Tesla BEVs over alternatives.

[Table 4 here]

[Table 5 here]

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 to other powertrains: for every 1 cent per mile increase in operating costs, CVs are 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^{28,24}. 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. Fig 3 shows the distribution of operating cost BEV is near the lower bound of the interquartile range of operating costs for the CVs.

While 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.gov⁸, 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 1/3 of PHEV owners may rarely charge their vehicle³⁰. If the estimated operating costs for certain PHEVs are mis-aligned 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 multivehicle 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.

[Figure 3 here]

Exploring Low BEV Mileage

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

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 that newer ones, though 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 to 2018; however, both models show a large, positive effect in model year 2019. While 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 a secondary rather than primary household car. 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 does include household demographics, and while 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. While households with 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 household.

Results from additional models examining household characteristics in the NHTS data are presented in Extended Data Table S4. Model 6a and 6c use CV cars and Model 6b uses Hybrid cars. While the NHTS data does 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 less miles than that of 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). While 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, though it very well could play a considerable role. This analysis also motivates 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 from⁴ and the electricity usage results from², which underestimate our results by 865 and 465 annual miles, respectively, and lower than the estimate of 8,838 annual miles from³⁷, which overestimates our results by 1,673 annual miles. The general alignment with the results from² 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 to 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 onboard 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^{22,41}. While this study is not immune from selection effects, the large sample size provides a more comprehensive estimate of historical BEV usage compared to 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^{36,33,23}. 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^{35,38,5}, 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, though the limitations of the listings data available prevent a strong conclusion about this phenomenon. Regardless of the underlying causes to 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 BEVs²¹. While 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 suggests that range is a major factor restricting BEV utilization^{33,29,41}. While 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 towards BEV range where the willingness to pay for additional mileage declines with increasing range¹⁴. Our study also reveals a similar nonlinear relationship where increasing driving range equates to an order of magnitude larger increase in annual VMT for lower-range compared to 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^{16,15,1,7}. We find that when increasing operating costs, less efficient vehicles are associated with a larger reduction in annual VMT compared to 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 that never sell 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 to 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 to 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 to 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. Popular SUV BEVs models such as Tesla Model Y were not available until later in 2020 and did not yet appear in the used market in the listing database. 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 comprised 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. While 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 gasolinepowered vehicles, and kWh per 100 miles for electricity-powered vehicles) are primarily from fueleconomy.gov⁸, with a small amount of missing values added from carsheet.io³. Monthly gasoline prices¹⁰ and annual average electricity prices⁹ in different states are from the U.S. Energy Information Administration (EIA). These data were joined onto the listings data based on the year, make, model, and trim.

Operating costs

Operating costs are estimated based on vehicle efficiencies and fuel prices at the U.S. 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 to 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 zipcode 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:

$$m = \alpha + \beta a + \gamma \boldsymbol{p} a + \boldsymbol{\epsilon} \tag{1}$$

where *m* is mileage (odometer readings in thousands of miles), *a* is age (in years), *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 γ 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):

$$m = \alpha + \beta a + \delta ac + \mu ar d + \rho a v + \sigma s + \epsilon$$
⁽²⁾

where *m* is mileage, *a* is age, *c* is operating cost (in cents per mile), *r* is electric driving range (in miles), *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), *v* is a matrix of dummy-coded vehicle model variables, *s* is a matrix of dummy-coded U.S. 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 *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 to 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:

$$m = \alpha + \beta a + \delta ac + \mu ad + \rho a \mathbf{h} + \nu \mathbf{y} + \sigma \mathbf{s} + \epsilon \tag{3}$$

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, \boldsymbol{y} is a matrix of dummy-coded variables representing the vehicle model year, and \boldsymbol{s} is a matrix of dummy-coded U.S. state variables.

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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.

Declarations of interests

The authors declare no competing interests.

References

- [1] I. M. Azevedo. Consumer end-use energy efficiency and rebound effects. *Annual Review of Environment and Resources*, 39:393–418, 2014.
- [2] F. Burlig, J. Bushnell, D. Rapson, and C. Wolfram. Low energy: Estimating electric vehicle electricity use. In *AEA Papers and Proceedings*, volume 111, pages 430–35, 2021.
- [3] carsheet.io. Carsheet the ultimate car spreadsheet, 2022. URL https://carsheet. io/.
- [4] L. W. Davis. How much are electric vehicles driven? Applied economics letters, 26(18): 1497–1502, 2019.
- [5] L. W. Davis. Electric vehicles in multi-vehicle households. Applied Economics Letters, pages 1–4, 2022.
- [6] L. W. Davis and J. M. Sallee. Should electric vehicle drivers pay a mileage tax? *Environmental and Energy Policy and the Economy*, 1(1):65–94, 2020.
- [7] P. De Haan, A. Peters, and R. W. Scholz. Reducing energy consumption in road transport through hybrid vehicles: investigation of rebound effects, and possible effects of tax rebates. *Journal of Cleaner Production*, 15(11-12):1076–1084, 2007.
- [8] U. DOE. U.s. department of energy, fueleconomy.gov web services, 2022. URL https: //www.fueleconomy.gov/feg/ws/.
- [9] U. EIA. U.s. energy information administration, electric sales, revenue, and average price, 2022. URL https://www.eia.gov/electricity/sales_revenue_price/.
- [10] U. EIA. U.s. energy information administration, monthly retail gasoline and diesel prices, 2022. URL https://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_nus_m.htm.
- [11] A. Elgowainy, J. Han, J. Ward, F. Joseck, D. Gohlke, A. Lindauer, T. Ramsden, M. Biddy, M. Alexander, S. Barnhart, I. Sutherland, L. Verduzco, and T. Wallington. Cradle-to-Grave Lifecycle Analysis of U.S. Light Duty Vehicle-Fuel Pathways: A Greenhouse Gas Emissions and Economic Assessment of Current (2015) and Future (2025-2030) Technologies. Technical Report ANL/ESD-16/7, 1254857, June 2016. URL http://www.osti.gov/servlets/purl/1254857/.
- [12] L. A.-W. Ellingsen, B. Singh, and A. H. Strømman. The size and range effect: lifecycle greenhouse gas emissions of electric vehicles. *Environmental Research Letters*, 11(5): 054010, 2016.
- [13] U. D. FHWA. U.s. department of transportation, federal highway administration, 2017 national household travel survey, 2017. URL https://nhts.ornl.gov.
- [14] L. Fridstrøm and V. Østli. The revealed preference for battery electric vehicle range. 2022.

- [15] K. Gillingham, A. Jenn, and I. M. Azevedo. Heterogeneity in the response to gasoline prices: Evidence from pennsylvania and implications for the rebound effect. *Energy Economics*, 52:S41–S52, 2015.
- [16] K. Gillingham, B. Spiller, and M. Talevi. The electric vehicle rebound effect. EPA NCEE, 2023.
- [17] D. Goebel and P. Plötz. Machine learning estimates of plug-in hybrid electric vehicle utility factors. Transportation research part D: Transport and environment, 72:36–46, 2019.
- T. R. Hawkins, O. M. Gausen, and A. H. Strømman. Environmental impacts of hybrid and electric vehicles—a review. *The International Journal of Life Cycle Assessment*, 17 (8):997–1014, Sept. 2012. ISSN 0948-3349, 1614-7502. doi: 10.1007/s11367-012-0440-9. URL http://link.springer.com/10.1007/s11367-012-0440-9.
- [19] S. P. Holland, E. T. Mansur, N. Z. Muller, and A. J. Yates. Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors. *American Economic Review*, 106(12):3700–3729, Dec. 2016. ISSN 0002-8282. doi: 10.1257/aer. 20150897. URL https://pubs.aeaweb.org/doi/10.1257/aer.20150897.
- [20] J. D. Jenkins, E. N. Mayfield, E. D. Larson, S. W. Pacala, and C. Greig. Mission netzero America: The nation-building path to a prosperous, net-zero emissions economy. *Joule*, 5(11):2755–2761, Nov. 2021. ISSN 25424351. doi: 10.1016/j.joule.2021.10.016. URL https://linkinghub.elsevier.com/retrieve/pii/S2542435121004931.
- [21] A. Jenn. Emissions benefits of electric vehicles in uber and lyft ride-hailing services. *Nature Energy*, 5(7):520–525, 2020.
- [22] W. Jia and T. D. Chen. Beyond adoption: Examining electric vehicle miles traveled in households with zero-emission vehicles. *Transportation Research Record*, page 03611981221082536, 2022.
- [23] M. F. Jung, D. Sirkin, T. M. Gür, and M. Steinert. Displayed uncertainty improves driving experience and behavior: The case of range anxiety in an electric car. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing* Systems, pages 2201–2210, 2015.
- [24] C. R. Knittel and R. Sandler. The welfare impact of second-best uniform-pigouvian taxation: evidence from transportation. *American Economic Journal: Economic Policy*, 10(4):211–242, 2018.
- [25] X. Li, C. Liu, and J. Jia. Ownership and usage analysis of alternative fuel vehicles in the united states with the 2017 national household travel survey data. *Sustainability*, 11(8):2262, 2019.
- [26] G. E. Metcalf et al. The distributional impacts of a vmt-gas tax swap. *NBER Chapters*, 2022.

- [27] J. J. Michalek, M. Chester, P. Jaramillo, C. Samaras, C.-S. N. Shiau, and L. B. Lave. Valuation of plug-in vehicle life-cycle air emissions and oil displacement benefits. *Proceedings of the National Academy of Sciences*, 108(40):16554–16558, Oct. 2011. ISSN 0027-8424, 1091-6490. doi: 10.1073/pnas.1104473108. URL http://www.pnas.org/cgi/doi/10.1073/pnas.1104473108.
- [28] C. Nehiba. Electric vehicle usage, pollution damages, and the electricity price elasticity of driving. *Pollution Damages, and the Electricity Price Elasticity of Driving (October* 5, 2022), 2022.
- [29] J. Neubauer and E. Wood. The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility. *Journal of power sources*, 257:12–20, 2014.
- [30] M. A. Nicholas, G. Tal, and T. S. Turrentine. Advanced plug-in electric vehicle travel and charging behavior interim report. 2017.
- [31] G. Pareschi, L. Küng, G. Georges, and K. Boulouchos. Are travel surveys a good basis for ev models? validation of simulated charging profiles against empirical data. *Applied Energy*, 275:115318, 2020.
- [32] N. S. Pearre, W. Kempton, R. L. Guensler, and V. V. Elango. Electric vehicles: How much range is required for a day's driving? *Transportation Research Part C: Emerging Technologies*, 19(6):1171–1184, 2011.
- [33] D. Pevec, J. Babic, A. Carvalho, Y. Ghiassi-Farrokhfal, W. Ketter, and V. Podobnik. A survey-based assessment of how existing and potential electric vehicle owners perceive range anxiety. *Journal of Cleaner Production*, 276:122779, 2020.
- [34] P. Plötz, S. Funke, P. Jochem, and M. Wietschel. Co2 mitigation potential of plug-in hybrid electric vehicles larger than expected. *Scientific reports*, 7(1):1–6, 2017.
- [35] S. S. Raghavan and G. Tal. Plug-in hybrid electric vehicle observed utility factor: Why the observed electrification performance differ from expectations. *International Journal of Sustainable Transportation*, 16(2):105–136, 2022.
- [36] N. Rauh, T. Franke, and J. F. Krems. Understanding the impact of electric vehicle driving experience on range anxiety. *Human factors*, 57(1):177–187, 2015.
- [37] L. Rush, Y. Zhou, and D. Gohlke. Vehicle residual value analysis by powertrain type and impacts on total cost of ownership. 5 2022. doi: 10.2172/1876197. URL https: //www.osti.gov/biblio/1876197.
- [38] S. Searle, N. Pavlenko, and N. Lutsey. Leading edge of electric vehicle market development in the united states: An analysis of california cities. *International Council on Clean Transportation*, 2016.

- [39] P. Shukla, J. Skea, R. Slade, A. A. Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, and J. Malley. Climate change 2022: Mitigation of climate change. Contribution of working group III to the sixth assessment report of the intergovernmental panel on climate change. 2022. doi: 10.1017/9781009157926. URL https: //www.ipcc.ch/report/sixth-assessment-report-working-group-3/.
- [40] J. Smart, W. Powell, S. Schey, et al. Extended range electric vehicle driving and charging behavior observed early in the ev project. SAE Technical paper, pages 01–1441, 2013.
- [41] G. Tal, S. S. Raghavan, V. C. Karanam, M. P. Favetti, K. M. Sutton, J. M. Ogunmayin, J. H. Lee, C. Nitta, K. Kurani, D. Chakraborty, M. Nicholas, and T. Turrentine. Advanced plug-in electric vehicle travel and charging behavior final report. 2020.
- [42] B. Tarroja, B. Shaffer, and S. Samuelsen. The importance of grid integration for achievable greenhouse gas emissions reductions from alternative vehicle technologies. *Energy*, 87:504–519, July 2015. ISSN 03605442. doi: 10.1016/j.energy.2015.05.012. URL https://linkinghub.elsevier.com/retrieve/pii/S0360544215005460.
- [43] J. H. Williams, A. DeBenedictis, R. Ghanadan, A. Mahone, J. Moore, W. R. Morrow III, S. Price, and M. S. Torn. The technology path to deep greenhouse gas emissions cuts by 2050: the pivotal role of electricity. *science*, 335(6064):53–59, 2012.
- [44] J. Xing, B. Leard, and S. Li. What does an electric vehicle replace? Journal of Environmental Economics and Management, 107:102432, 2021.
- [45] J. Zhao and L. Mattauch. When standards have better distributional consequences than carbon taxes. *Journal of Environmental Economics and Management*, 116:102747, 2022.

Figures and Tables



Fig. 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 grey) is shown for comparison in each sub-figure



 (b) SUVs

3 4 5 6 7

Vehicle age (years)

 Fig. 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 2b for SUVs), and the dotted lines are extrapolations beyond the range of observed data.



Fig. 3 | Distribution of operating costs across cars and SUVs in sample by powertrain.

Study	Estimated Annual VMT	Sample Location	$\begin{array}{l} \text{Sample} \\ \text{Size}^{*} \end{array}$	Data Year(s)	Data Source
Davis $(2019)^4$	6,300	U.S.	436	2017	NHTS^\dagger
Burlig et al. $(2021)^2$	6,700	California	57,290	2014 - 2017	Household electricity meter readings
Rush et al. $(2022)^{37}$	8,838	U.S.	Unknown	2013 - 2021	Edmunds vehicle listings
Jia and Chen $(2022)^{22}$	10,000	California	184	2019	2019 California Vehicle Survey
Tal et al. $(2020)^{41}$	12,522	California	100	2015 - 2018	On-board vehicle sensors
This Study	7,165 (cars)	U.S.	175,773 (cars)	2016 - 2022	Used vehicle listings
(2023)	$\begin{array}{c} 10,587\\ (\mathrm{SUVs}) \end{array}$		$\begin{array}{c} 12,\!623 \\ (\mathrm{SUVs}) \end{array}$		

*BEV sedans only.

[†]National Household Travel Survey¹³.

 ${\bf Table \ 1} \ | \ {\rm Summary \ of \ estimated \ BEV \ mileage \ from \ previous \ studies}.$

	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 (ma	iles)				
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 (ma	iles)				
mean	_	_	_	204	266
sd	_	_	_	0	31
\min	_	_	_	204	200
max	_	_	—	204	371

 $\label{eq:Table 2} \textbf{Table 2} ~|~ \text{Summary statistics of used car and SUV listings}.$

	Cars		SUVs		
	Model 1a	Model 1b	Model 2a	Model 2b	
Intercepts					
(Intercept)	0.716^{***}	0.716^{***}	-4.104^{***}	-4.104^{***}	
	(0.019)	(0.019)	(0.018)	(0.018)	
powertrain_hybrid	-0.124	-0.124	0.634^{*}	0.634^{*}	
	(0.093)	(0.093)	(0.295)	(0.295)	
$powertrain_phev$	-4.005^{***}	-4.005^{***}			
	(0.203)	(0.203)			
powertrain_bev	-0.302	. ,	-3.081^{***}		
	(0.177)		(0.710)		
powertrain_bev_non_te	esla	0.777^{***}		-6.371	
		(0.219)		(3.657)	
powertrain_bev_tesla		-1.291^{***}		2.722***	
		(0.299)		(0.800)	
age_years	11.642***	11.642***	12.979***	12.979***	
	(0.004)	(0.004)	(0.004)	(0.004)	
Interactions with age_	years				
powertrain_hybrid	0.299***	0.299***	-0.853^{***}	-0.853^{***}	
- •	(0.019)	(0.019)	(0.068)	(0.068)	
powertrain_phev	-0.529^{***}	-0.529^{***}		~ /	
	(0.046)	(0.046)			
powertrain_bev	-4.477^{***}	× ,	-2.795^{***}		
	(0.040)		(0.186)		
powertrain_bev_non_te	esla	-5.407^{***}	. /	-4.425^{***}	
		(0.050)		(1.344)	
powertrain_bev_tesla		-2.856^{***}		-4.009^{***}	
		(0.067)		(0.202)	
Num. obs.	12,511,667	12,511,667	11,391,430	11,391,430	
\mathbb{R}^2	0.405	0.406	0.480	0.480	

Table 3 | Model coefficients from linear models of vehicle mileage versus age with power-train interactions. Mileage is in units of 1,000 miles.

Powertrain:	Model 3a BEV	Model 3b PHEV	Model 3c Hybrid	Model 3d Conventional
age_years	5.835***	12.902^{***}	13.372^{***}	11.518***
	(0.422)	(0.399)	(0.330)	(0.033)
Operating cost and	d range interact	ions with age_years		
cents_per_mile	-0.059^{**}	0.522***	0.071^{*}	-0.140^{***}
	(0.020)	(0.039)	(0.030)	(0.002)
range	0.009***	-0.182^{***}		
	(0.001)	(0.011)		
range*range_low	0.055***			
(<100mi)	(0.010)			
range*range_mid	0.033***			
(100 - 200mi)	(0.009)			
Select model intere	actions with age	$_years$		
Reference	Nissan	Toyota	Honda	BMW
level:	Leaf	Prius Prime	Accord	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^{***}	1.723^{***}
			(0.393)	(0.026)
fusion hybrid			-3.510^{***}	
			(0.334)	
corolla				0.359^{***}
				(0.028)
mustang				-1.418^{***}
				(0.031)
outback				3.178^{***}
				(0.031)
Num. obs.	175,773	128,850	528,674	11.643.966
\mathbb{R}^2	0.412	0.460	0.394	0.449

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

Powertrain:	Model 4a BEV	Model 4b Hybrid	Model 4c Conventional
age_years	$ \begin{array}{c} 12.104^{***} \\ (1.885) \end{array} $	$\begin{array}{c} 12.867^{***} \\ (0.979) \end{array}$	$16.644^{***} \\ (0.049)$
Operating cost and range int	eractions with ag	e_years	
cents_per_mile	-0.343***	-0.257^{***}	-0.279^{***}
	(0.095)	(0.072)	(0.003)
range	-0.005		
	(0.008)		
Select model interactions wit	h age_years		
Reference	Audi	Porsche	Toyota
level:	e-tron	Cayenne	4runner
model x	0.477		
	(0.988)		
model y	4.926		
	(9.001)		
escape		-7.588^{***}	-1.188^{***}
		(0.651)	(0.030)
highlander		2.705^{***}	-0.328^{***}
		(0.399)	(0.033)
rav4		4.450	1.847^{***}
		(2.447)	(0.146)
expedition			2.096***
			(0.058)
wrangler			-3.475^{***}
			(0.039)
Num. obs.	13,243	44,190	11,333,997
\mathbb{R}^2	0.376	0.492	0.519

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

Supplemental information



Fig S1 | 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. CVs are in grey while Tesla BEVs are in blue and Non-Tesla BEVs are in green.

Powertrain	Make	Model	Count	Percent	Cumulative Percent
	Nissan	Leaf	84,144	0.260	0.260
	Chevrolet	Bolt	48,801	0.151	0.412
	Tesla	Model S	48,773	0.151	0.562
	Tesla	Model 3	39,783	0.123	0.686
	BMW	I3	38,136	0.118	0.804
	Fiat	500e	12,971	0.040	0.844
BEV	Volkswagen	e-Golf	8,747	0.027	0.871
	KIA	Niro	$7,\!350$	0.023	0.894
	Porsche	Taycan	$5,\!374$	0.017	0.910
	Chevrolet	Spark	4,706	0.015	0.925
	KIA	Soul	4,360	0.013	0.938
	Ford	Focus	4,152	0.013	0.951
	Smart	Fortwo	3,683	0.011	0.963
	Chevrolet	Volt	80,282	0.399	0.399
	Ford	Fusion	49,474	0.246	0.645
		Energi			
	Toyota	Prius	41,228	0.205	0.850
		Prime			
	Toyota	Prius	$13,\!639$	0.068	0.918
PHEV		Plug-In			
	BMW	i8	6,014	0.030	0.948
	Cadillac	ELR	2,320	0.012	0.960
	Hyundai	Sonata	2,294	0.011	0.971

 ${\bf Table \ S1} \ | \ {\rm Counts \ of \ car \ model \ listings \ included \ in \ analyses.}$

Powertrain	Make	Model	Count	Percent	Cumulative Percent
	Toyota	Prius	424,619	0.379	0.379
	Ford	Fusion	130,801	0.117	0.495
	Toyota	Prius C	68,535	0.061	0.557
	Toyota	Camry	64,860	0.058	0.614
	Hyundai	Sonata	58,011	0.052	0.666
	Lexus	ct	42,354	0.038	0.704
	Lincoln	MKZ	36,826	0.033	0.737
HYBRID	Ford	Fusion	30,219	0.027	0.764
	Honda	Accord	28,161	0.025	0.789
	Honda	Insight	$23,\!201$	0.021	0.809
	KIA	Niro	21,094	0.019	0.828
	KIA	Optima	20,965	0.019	0.847
	Toyota	Prius V	20,144	0.018	0.865
	Lexus	\mathbf{ES}	18,261	0.016	0.881
	Honda	Civic	18,253	0.016	0.898
	Toyota	Avalon	16,803	0.015	0.913
	Buick	Lacrosse	16,234	0.014	0.927
	Chevrolet	Malibu	11,575	0.010	0.937
	Honda	CR-Z	11,236	0.010	0.947

Table S1 ~|~ Counts of car model listings included in analyses. (cont.)

Powertrain	Make	Model	Count	Percent	Cumulative Percent
	Toyota	Camry	1,809,448	0.050	0.050
	Honda	Accord	1,761,206	0.049	0.099
	Honda	Civic	$1,\!670,\!320$	0.046	0.145
	Toyota	Corolla	1,539,561	0.043	0.188
	Nissan	Altima	1,369,133	0.038	0.226
	Nissan	Sentra	$1,\!055,\!638$	0.029	0.255
	Ford	Fusion	1,055,271	0.029	0.284
	Chevrolet	Malibu	976, 393	0.027	0.311
	Hyundai	Elantra	968,141	0.027	0.338
	Hyundai	Sonata	$930,\!253$	0.026	0.364
	Chevrolet	Cruze	862,213	0.024	0.388
	Ford	Mustang	$746,\!479$	0.021	0.409
CV	BMW	3 Series	715,274	0.020	0.428
	Volkswagen	Jetta	$648,\!119$	0.018	0.446
	Subaru	Outback	608,624	0.017	0.463
	KIA	Optima	$608,\!198$	0.017	0.480
	KIA	Soul	$550,\!557$	0.015	0.495
	Dodge	Charger	$508,\!984$	0.014	0.509
	Chevrolet	Camaro	490,499	0.014	0.523
	Mazda	Mazda3	479,885	0.013	0.536
	KIA	Forte	444,832	0.012	0.549
	Dodge	Challenger	$421,\!275$	0.012	0.560
	BMW	5 Series	379,421	0.011	0.571
	Nissan	Maxima	372,633	0.010	0.581
	Lexus	ES	368,555	0.010	0.591

Table S1 ~|~ Counts of car model listings included in analyses.~(cont.)

Powertrain	Make	Model	Count	Percent	Cumulative Percent
	Tesla	Model X	16,246	0.194	0.194
BEV	Audi	e-tron	10,826	0.129	0.323
	Tesla	Model Y	5,261	0.063	0.704
	Toyota	RAV4	47,039	0.240	0.240
	Lexus	RX	38,518	0.197	0.437
HYBRID	Toyota	Highlander	28,462	0.145	0.582
	Ford	Escape	9,165	0.047	0.683
	BMW	X5	6,238	0.032	0.801
	Subaru	XV	6,005	0.031	0.832
		Crosstrek			
	Porsche	Cayenne	4,538	0.023	0.855
	Lexus	NX	3,904	0.020	0.875

 ${\bf Table \ S2} \ | \ {\rm Counts \ of \ SUV \ model \ listings \ included \ in \ analyses.}$

Powertrain	Make	Model	Count	Percent	Cumulative Percent
	Honda	CR-V	1,706,212	0.049	0.049
	Toyota	RAV4	1,507,128	0.043	0.092
	Ford	Escape	1,488,216	0.043	0.135
	Nissan	Rogue	1,073,001	0.031	0.166
	Chevrolet	Equinox	930,195	0.027	0.192
	Jeep	Grand	927,907	0.027	0.219
		Chero- kee			
	Tovota	Highlander	882,930	0.025	0.244
	Jeep	Cherokee	877,204	0.025	0.269
	Chevrolet	Traverse	823,064	0.024	0.293
	Jeep	Wrangler	799,060	0.023	0.316
	1	Unlim- ited	,		
	Honda	Pilot	777,143	0.022	0.338
	Ford	Explorer	755,941	0.022	0.360
	KIA	Sorento	641,640	0.018	0.378
	Toyota	4runner	641,617	0.018	0.396
	Ford	Edge	630,817	0.018	0.415
	Lexus	RX	$605,\!245$	0.017	0.432
	Subaru	Forester	587,590	0.017	0.449
	Hyundai	Tucson	$580,\!673$	0.017	0.465
CV	Hyundai	Santa Fe	577,097	0.017	0.482
	Jeep	Compass	566,082	0.016	0.498
	Gmc	Acadia	529,328	0.015	0.513
	Nissan	Pathfinder	480,441	0.014	0.527
	KIA	Sportage	416,946	0.012	0.539
	Buick	Enclave	406,382	0.012	0.551
	Mazda	CX-5	$395,\!472$	0.011	0.562
	Dodge	Journey	382,336	0.011	0.573
	Volkswagen	Tiguan	382,204	0.011	0.584
	Gmc	Terrain	$372,\!629$	0.011	0.595
	Acura	MDX	371,089	0.011	0.605
	Chevrolet	Trax	361,101	0.010	0.616
	Buick	Encore	361,083	0.010	0.626
	Nissan	Murano	360,982	0.010	0.636
	Jeep	Patriot	$359,\!392$	0.010	0.647
	Ford	Expedition	355,704	0.010	0.657
	Jeep	Wrangler	$350,\!373$	0.010	0.667

Table S2 | Counts of SUV model listings included in analyses. (cont.)

1 Creente	Powertrain	Make	Model	Count	Percent	Cumulative Percent
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Table S2 ~|~ Counts of SUV model listings included in analyses. (cont.)

Powertrain:	Model 5a	Model 5b	Model 5c	Model 5d
age_years	5.835^{***}	6.639***	1.813**	3.746^{***}
	(0.422)	(0.449)	(0.573)	(0.632)
age_years^2	· · · ·	-0.093^{***}	· · · ·	-0.156^{***}
0.0		(0.018)		(0.022)
Operating cost as	nd range interac	ctions with age_u	ears	· · · · ·
cents_per_mile	-0.059^{**}	-0.058^{**}	-0.033	-0.033
Ĩ	(0.020)	(0.020)	(0.022)	(0.022)
range	0.009***	0.007***	0.016***	0.016***
0	(0.001)	(0.001)	(0.002)	(0.002)
range*range_low	0.055***	0.034**	-0.031	-0.038^{*}
(<100mi)	(0.010)	(0.011)	(0.016)	(0.016)
range*range_mid	0.033***	0.032***	-0.016	-0.014
(100-200mi)	(0.009)	(0.009)	(0.010)	(0.010)
Select model inte	eractions with ad	ge_years (referend	ce level: Nissan	Leaf)
bolt ev	-5.672^{***}	-5.495^{***}	-4.582^{***}	-4.507^{***}
	(0.293)	(0.295)	(0.352)	(0.352)
model 3	1.056***	1.200***	1.425***	1.512***
	(0.292)	(0.293)	(0.328)	(0.328)
model s	0.538^{*}	0.968***	1.240***	1.340***
	(0.244)	(0.257)	(0.327)	(0.327)
Model year inter	actions with age	-years (reference	e level: my2012)	
my2013			1.431***	1.311***
v			(0.158)	(0.159)
my2014			1.852***	1.580***
-			(0.195)	(0.199)
my2015			1.626***	1.175***
			(0.194)	(0.204)
my2016			1.097^{***}	0.473^{*}
			(0.200)	(0.218)
my2017			0.184	-0.616^{*}
			(0.237)	(0.261)
my2018			1.531^{***}	0.597
			(0.296)	(0.323)
my2019			4.146^{***}	3.021^{***}
			(0.469)	(0.494)
Num. obs.	175,773	175,773	171,701	171,701
\mathbb{R}^2	0.412	0.413	0.412	0.412

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

Table S3 | Coefficients from linear models estimated on BEV cars. Age is interacted with operating costs (in cents per mile), vehicle model, electric driving range, and vehicle model year fixed effects. 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.

Powertrain:	Model 6a Conventional	Model 6b Hybrid	Model 6c Conventional
age_years	12.839***	15.157***	12.332***
	(0.875)	(3.964)	(0.880)
Interactions with age_years			
cents_per_mile	-0.243***	-0.378	-0.239^{***}
	(0.040)	(0.346)	(0.040)
secondary vehicle	-1.063^{***}	-2.169^{*}	-1.586^{***}
	(0.180)	(0.849)	(0.309)
HHSIZE 3	1.419^{***}	1.096	1.501^{***}
	(0.230)	(1.035)	(0.232)
HHSIZE 4	1.541^{***}	1.356	1.627^{***}
	(0.265)	(1.195)	(0.268)
HHSIZE 5	2.644^{***}	2.019	2.676^{***}
	(0.447)	(2.248)	(0.451)
HHSIZE 6+	0.340	0.661	0.446
	(0.703)	(4.386)	(0.711)
Num. obs.	32,169	2,139	32,169
\mathbb{R}^2	0.368	0.409	0.358

Table S4 | Coefficients from linear models estimated on the 2017 NHTS data with state and model year fixed effects (cars only). Age is interacted with operating costs (in cents per mile), dummy coefficients for household size, and a dummy coefficient for whether the car is a "secondary" vehicle, defined as any vehicle with less than the highest odometer reading in a household in Models 6a and 6b, and any vehicle with less than the top two highest odometer readings in a household in Model 6c. For conciseness, intercept terms are omitted.