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# How Much Are Electric Vehicles Driven? Depends on the EV

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***How Much are Electric Vehicles Driven? Depends on the EV***

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*Abstract*

We use the 2017 National Household Travel Survey to investigate whether all-electric vehicles (EVs) are driven less than their counterfactual alternative in the US as hypothesized by Davis (2019). We find that selection effects reduce to a small degree the driving differential between EVs and gasoline or diesel powered vehicles. The dominant factor affecting annual miles driven is battery range. Once one limits the analysis to EVs with a range of 100 miles or more, the differences between EVs and internal combustion engine vehicles disappear. Given the rapidly increasing range of new EVs, we conclude that any difference in annual driving between EVs and other vehicles will be insignificant going forward. This has important implications for policy modeling including such policies as a revenue neutral VMT-Gas Tax swap.

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**Introduction**

Transportation is the single largest source of greenhouse gas emissions in the United States.[1] Given that, a key element of federal climate policy is to shift personal transportation away from gasoline and diesel fueled vehicles towards electric vehicles (EVs)[2]. This reduces greenhouse gas emissions to the extent that electricity is increasingly produced from zero-carbon sources. The recently enacted Inflation Reduction Act includes numerous incentives both for personal investments in EVs and plug-in hybrid (PHEV) vehicles as well as for personal and business investments in zero-carbon electricity generation capital .[3]

Swapping out gasoline and diesel vehicles with electric vehicles is an effective decarbonization strategy, conditional on the decarbonization of the electric grid. It raises a number of important policy questions including, for example, how the federal government raises revenue for the Highway Trust Fund. Currently, all revenue from the federal motor vehicle fuel excise tax is earmarked for this fund. As more EVs are purchased, fuel excise tax revenue will fall. This has led to renewed interest in enacting a vehicle-miles-traveled (VMT) tax to replace lost motor vehicle fuel excise tax revenue. Recent papers by Metcalf (forthcoming) and Glaeser et al. (forthcoming) explore the distributional implications of a VMT-Gas Tax swap. Importantly, both papers assume that households shifting from gasoline or diesel-powered vehicles to electric vehicles do not change their driving behavior (other than perhaps driving changes due to a rebound effect[4]).

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[1] In 2020, transportation accounted for 27% of total US greenhouse gas emissions, the highest of any sector: https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions.

[2] Throughout this paper, we refer to all-electric vehicles as electric vehicles (or EVs). When discussing other types of electric vehicles, we'll refer to them explicitly as plug-in hybrids (PHEV) or hybrid vehicles. In part, this is due to the industry trend towards all-electric vehicles, as evidenced by General Motors's decision to retire the Chevrolet Volt PHEV in favor of the all-electric Bolt. See GM CEO Mary Barra's remarks at CERAWeek in 2018, for example: https://news.gm.com/newsroom.detail.html/Pages/news/us/en/2018/mar/0307-barra-speech.html.

[3] Here's a summary of the Inflation Reduction Act: https://www.whitehouse.gov/briefing-room/statements-releases/2022/08/15/by-the-numbers-the-inflation-reduction-act/

[4] The rebound effect is the increase in driving demand induced by a decline in the price of driving per mile. See Gillingham et al. (2016).

This assumption is challenged in a recent paper by Davis (2019) that argues "electric vehicles are driven considerably less on average than gasoline- and diesel-powered vehicles" (p. 1497). Davis correctly notes that "… the less electric vehicles are driven, the smaller the environmental benefits from electric vehicle adoption." In addition to smaller environmental benefits, estimates of driving and market penetration of EVs in the future would influence EV-related policy decisions and analyses, with potentially important distributional implications. If higher income households are more likely to own EVs, and if they drive fewer miles upon switching from a gasoline or diesel-powered vehicle, then the burden of a revenue-neutral VMT-gas tax swap will fall more heavily on lower-income households, relative to an analysis that assumes miles driven does not change when an EV replaces a gasoline or diesel-powered vehicle.

As with the VMT-gas tax swap, any analysis analyzing and estimating EV impacts relies on a decent understanding of EV driving behavior. This is reflected in the studies that have cited Davis's results. In developing counterfactual simulations of the environmental benefits of subsidies for EV purchases, Xing et al. (2021) cite Davis's result to support their lower lifetime VMT assumptions for EVs relative to gasoline- and diesel-powered vehicles. Nunes et al. (2022) estimate required EV minimum lifetime driving behavior to ensure the purchase of an EV leads to lower greenhouse gas emissions. Their research question is motivated, in part, by the concern that EVs may not be driven as much as the vehicles they replace. A recent study by Burlig et al. (2021) also finds evidence of low driving behavior by EVs. Their evidence is indirect as it estimates increased residential electricity load in a sample of California residential electricity customers to infer miles driven by EVs. They find that EVs are driven approximately 6,700 miles a year, a result similar to findings in Davis's study. While their study is intriguing, it does depend on a number of important assumptions as the authors move from residential electricity consumption to actual vehicle-miles-traveled for the vehicles in their sample. On the other hand , Chakraborty et al. (2022) find that PEVs in California are not driven less relative to conventional vehicles vehicles. Their results indicate that range and charging infrastructure are the two main drivers of the VMT for PEVs.

Davis makes an important point about the relevant counterfactual for EV driving behavior, but we think the evidence contained in the 2017 National Household Travel Survey (NHTS), the data that he uses for his analysis is a bit more nuanced than appears at first glance. Our analysis of the same data suggests that EV driving range is a key factor in explaining differences in annual mileage for EVs versus gasoline- or diesel-powered vehicles; if one focuses on long-range EVs, we find the driving difference goes away. Given the marked improvement in battery range for EVs, an improvement that is likely to continue, we are more sanguine about the benefits of EV purchase policies to reduce emissions than is suggested by Davis's study.[5]

[5] In fairness to Davis, he does acknowledge that "[l]imited range, particularly for the first generation of electric vehicles, has likely played a key role [in explaining low annual mileage], so this pattern may change over time as more long-range electric vehicles are introduced." (pp. 1497-8) His paper, however, does not explore this hypothesis.

**Measuring annual VMT**

Like Davis, we use data from the 2017 National Household Travel Survey (NHTS). This survey provides data on household travel patterns, vehicle ownership, household characteristics, and specific trips that take place during designated "travel days." We use data from the vehicles file which contains information on 256,115 vehicles owned by 129,696 households.

Several measures in the NHTS survey could be used to measure annual miles driven. While the NHTS collects a self-reported measure of annual vehicle miles traveled (ANNMILES), only three-quarters of vehicles self-report VMT. Moreover, the self-reported measure is subject to error. The NHTS, therefore, uses this measure, when available, along with a single odometer reading, vehicle age, and other vehicle and household information to construct an estimate of annual vehicle miles traveled. For his analysis, Davis uses an alternative measure by dividing the odometer reading by the vehicle age (in years).[6] Going forward, we will refer to this annual VMT estimate as "Annual Average VMT." One problem with using this measure is that the NHTS documents that annual driving declines with vehicle age. Creating an annual measure simply by dividing the odometer reading by vehicle age will lead to a downward bias in the estimated annual VMT measure for newer vehicles relative to older vehicles.[7] As a result, this will bias annual miles driven for EVs down relative to other vehicles.[8] Additionally, since the Annual Average VMT is estimated using vehicle age in years, it does not account for differences in

[6] Davis used this measure as the NHTS estimate of annual VMT was not available when he did his analysis (personal communication, May 2022).

[7] The NHTS models annual driving as declining according to a quadratic function. We can closely approximate that relationship with the functional form for driving in year $t$, $M_t = MD^{t-1}$, where $D < 1.$ In the appendix, we show that for a vehicle that is $k$ years old, the ratio of annual average VMT to actual VMT in year $k$ is an increasing function of $k$.

[8] This might seem counterintuitive, but note that annual VMT is different than an average VMT. While annual VMT measures miles traveled by a vehicle in its *current* year, average VMT constructed by dividing the odometer reading by vehicle age estimates *average annual lifetime* miles. Based on *current* driving, a younger vehicle's VMT is expected to be greater than an older vehicle's VMT. However, the average VMT measure for an older vehicle will reflect relatively more miles than the vehicle drove in its *current* year, since the average also includes the higher annual miles the vehicle drove when it was younger. See Appendix B for a mathematical intuition for this.

months driven. A vehicle driven for 13 months would have the same treatment as one driven for 23. Younger vehicles, which EVs tend to be, would be more sensitive to this crude estimation.

To address this downward trend in annual driving as vehicles age, the NHTS data constructors fit a curve of self-reported driving to vehicle-age and vehicle-age squared for all new and used vehicles and adjust annual miles driven to account for this decline. The result is to shift some of the total miles driven, as reported by the odometer reading towards the first few years of a vehicle's life. We refer to this measure as "Adjusted Annual Average VMT."[9] The fourth measure of annual VMT, labelled BESTMILE in the NHTS, which we refer to as "NHTS Reported VMT", takes the Adjusted Annual Average VMT measure as its starting point and makes further adjustments based on household characteristics including employment and education levels of the primary vehicle driver, community information (e.g. rural, urban), and household size, among other variables.[10] Below we will report estimates using all four annual VMT measures.

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[9] While not reported in the publicly available NHTS dataset, the NHTS provided us with these estimates. In the documentation, this is the variable ODOMMILES.

[10] The construction of this variable (BESTMILE) is detailed in the NHTS publication *Best Estimate of Annual Vehicle Mileage for 2017 NHTS Vehicles* found at https://nhts.ornl.gov/documentation. We summarize and comment on their approach in the Appendix.

**EVs Are Driven Less. Why?**

In our analysis, we exclude motorcycles, recreational vehicles (RVs) and trucks other than pickup trucks. Our analysis thus focuses on automobiles, SUVs, vans, and pickup trucks. We drop observations with unexpectedly large (or small) values for NHTS Reported Annual Miles driven as well as vehicles with unknown age or fuel type. We are left with 220,329 vehicles to analyze. Because there are very few EVs more than six years old, we also limit our analysis to vehicles no more than six years old. This reduces the dataset to roughly 85,000 vehicles.

**Table 1**. Miles Driven per Year: Descriptive Statistics

| | No. of Observations | Mean | Standard Deviation |
|---|---|---|---|
| EVs | 416 | 6,489 | 4,076 |
| PHEVs | 408 | 7,755 | 4,881 |
| ICEs | 79,224 | 10,826 | 8,618 |
| Hybrids | 2,564 | 11,470 | 7,059 |

Note: This table reports descriptive statistics for miles driven per year by vehicle type in the 2017 NHTS for all vehicles six or fewer years old. All statistics are calculated using sampling weights.

**Table 2.** Are Electric Vehicles Driven Less Than Other Vehicles?

| | Electric Vehicles | All Other Vehicles | p-value (1) vs (2) |
|---|---|---|---|
| Entire Sample | 7,131 | 10,848 | 0.00 |
| All-Electrics Only | 6,489 | 10,848 | 0.00 |
| Plug-in Hybrids Only | 7,755 | 10,848 | 0.00 |
| Single-Vehicle Households | 7,391 | 10,335 | 0.00 |
| Multiple-Vehicle Households | 7,103 | 10,978 | 0.00 |
| California Only | 7,209 | 10,322 | 0.00 |
| Excluding California | 7,074 | 10,908 | 0.00 |

Note: This table reports average miles driven per year for electric- and non-electric-vehicles in the 2017 NHTS for all vehicles six or fewer years old. The last column reports p-values from tests that the means in the two subsamples are equal. All estimates are calculated using sampling weights.

Tables 1 and 2 replicate the corresponding tables in Davis for our smaller data set using his measure of Annual Average VMT. Our summary statistics in Table 1 closely match those of Davis. Where Davis, for example, reports mean driving of 6,300 miles for all-electric vehicles, we report a mean of 6,500 miles (after rounding to the nearest 100 as per Davis). We conclude from this that the results in Davis's 2019 paper are unaffected by limiting the data set to newer vehicles (less than or equal to six years old) with this measure. Table 2 also closely matches the results in Davis's paper. The one entry that looks different is all other vehicles for California where we report average miles driven of 10,322 versus 9,800 in Davis's paper.

We next turn to results using the other measures of annual miles driven. Table 3 reports comparisons of vehicle miles traveled for our four measures where we compare the average driving for different types of electric or hybrid vehicles to vehicles with internal combustion engines (gasoline or diesel). Using Davis's annual VMT measure (column 2), we see that all-electric vehicles are driven nearly 3,800 miles less than gasoline or diesel powered vehicles. This is less than the 4,359 mile difference for all-electric vehicles versus all-other vehicles in Table 2 (second row: 6,489 versus 10,848 miles) since Table 3 is comparing various electric vehicles to gasoline or diesel powered vehicles only.

**Table 3.** Electric Vehicle Driving Relative to Gasoline and Diesel-Powered Vehicles

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Type of Electric Vehicle | Self-Reported VMT | Average VMT | Adj. Average VMT | NHTS Reported VMT |
| Plug-In Hybrid | -1,190 | -2,670 | -2,916 | -798 |
| All-Electric | -3,080 | -3,792 | -4,233 | -2,485 |
| Hybrids | 2,091 | 689 | 1,454 | 860 |
| $R^2$ | 0.0031 | 0.0033 | 0.0027 | 0.0010 |
| Number of Observations | 65,219 | 72,550 | 72,534 | 83,172 |

Note: This table reports the difference in driving between the vehicles identified in the first column and gasoline or diesel operated vehicles. The *p*-values for the difference in driving between each type of vehicle and gasoline or diesel operated vehicles in all cases is less than 0.01. Each column reports a different measure of annual vehicle miles traveled. All estimates are calculated using sampling weights.

Regardless of our measure of annual driving, the results are consistent and statistically significant at the 99 percent level. All-electric vehicles (EVs) are driven between 2,500 and 4,200 fewer miles annually than gasoline or diesel powered vehicles when not controlling for owner or vehicle characteristics (other than fuel type). Plug-in hybrid vehicles are driven anywhere between 800 and 2,900 fewer miles than gasoline or diesel powered vehicles. Again, the difference is highly statistically significant. Like Davis, we find it puzzling that plug-in hybrids are driven fewer miles. Davis conjectures that this might be a sample selection issue as drivers choosing plug-in hybrids may wish to drive them primarily on electricity, thereby affecting who buys these vehicles and how they drive them. We also find, as does Davis, that conventional hybrids are driven more than gasoline or diesel powered vehicles, anywhere from 690 to 2,100 miles depending on the measure of annual driving.

What explains the difference in driving between EVs and gasoline or diesel vehicles? One hypothesis is selection. Environmentally-conscious drivers may simply drive less and prefer EVs. Drivers in urban areas, where people drive less may prefer EVs. EVs may be secondary vehicles for some. While we cannot fully test for these preferences, we use the available set of household-level and driver-specific information to test the selection hypothesis. Accordingly, we run regressions of VMT on vehicle type while controlling for household characteristics. In particular, we control for driver characteristics including age, sex, race, educational level, household income, whether the driver has a medical condition, is physically active or not, is employed (part-time or full-time), and is able to work from home or not. We also control for the number of vehicles per driver in the household,[11] whether the household is in an urban or rural area, and include controls for census region by size of metropolitan statistical area (MSA) by presence of an urban transit system. We also control for vehicle age and age squared as well as the length of time the vehicle has been owned by the household.

[11] Some studies, including Davis (2019), discuss whether EV ownership by single-vehicle vs. multiple vehicle households may be a potential explanation for the VMT differences. Controlling for the vehicle-driver ratio, measured by the number of vehicles per driver in the household, may be another way to test this hypothesis. We find that this doesn't make the difference disappear. There aren't enough single-vehicle households that own EVs in the NHTS dataset for us to meaningfully test the hypothesis comparing EV VMTs for single-vehicle vs. multiple vehicle households.

**Table 4.** Electric Vehicle Driving Relative to Gasoline and Diesel-Powered Vehicles: Household and Vehicle Controls

| Type of Electric Vehicle | (1) Self-Reported VMT | (2) Average VMT | (3) Adj. Average VMT | (4) NHTS Reported VMT |
|---|---|---|---|---|
| Plug-in Hybrid | -1,229*** | -1,957*** | -3,049*** | -669* |
| All-Electric | -2,731*** | -2,780*** | -4,040*** | -2,191*** |
| Hybrids | 2,541*** | 1,151*** | 2,167*** | 1,281*** |
| $R^2$ | 0.11 | 0.17 | 0.11 | 0.09 |
| Number of Observations | 62,932 | 69,844 | 69,832 | 79,694 |

Note: This table reports the difference in driving between the vehicles identified in the first column and gasoline or diesel operated vehicles in regressions controlling for household and vehicle characteristics. Each column reports a different measure of annual vehicle miles traveled. All estimates are calculated using sampling weights. The *p*-values are indicated by stars: *** p<0.01, ** p<0.05, * p<0.10

Table 4 presents the results and suggests that sample selection has some effect on annual miles driven for EVs and Hybrids. Comparing Tables 3 and 4, we find that the estimated differences in driving between either of those vehicle types and gasoline and diesel powered vehicles becomes less negative (Evs) or more positive (Hybrids). The estimates for plug-in hybrids in some cases are larger and in other cases smaller. For EVs, the changes are modest. The results for the NHTS reported VMT don't change as much compared to those of the other three VMT measures since the NHTS reported measure adjusts for household and primary driver characteristics.[12]

But sample selection does not fully explain the differences, based on available measures. Even after controlling for household, vehicle, and regional characteristics, both EVs and PHEVs are driven less than gasoline and diesel-powered vehicles. For EVs, the difference ranges from 2,200 to 4,000 miles, depending on the measure of annual VMT. Above, we conjectured that driving in EVs would be biased

[12] Whether a final VMT measure should include this adjustment depends on the analytical context, but that the final VMT measure of NHTS reported data does this is something that future users of NHTS data should keep in mind.

down using average VMT given the finding that cars are driven fewer miles annually as they age. Adjusting for the age factor in column 3 of Table 4 actually leads to larger declines in annual driving than when simply dividing the odometer reading by vehicle age (column 2). As Davis finds, conventional hybrids are driven more than gasoline and diesel vehicles.

Another possible explanation of the lower annual VMT is battery range for EVs. Davis notes this but does not test this hypothesis. In Table 5, we add an indicator variable for whether an EV has battery range of 100 miles or less to our regression.[13] The estimate in the second row (All-Electric) now represents the difference in annual VMT between long-range (more than 100 miles per charge) EVs versus gasoline and diesel vehicles. The estimates in the middle two columns for EVs (row 2) continue to be negative but are smaller in magnitude and less statistically significant. Using the first three columns, (self-reported VMT, average VMT, and adjusted average VMT ), we cannot reject the hypothesis that the difference is zero at any reasonable level of significance. The magnitude of these differences in the first (self-reported VMT) and third (Adjusted average VMT) columns is also very close to zero. Finally, using the NHTS reported VMT (column 4), the estimate is now positive with a *p*-value of less than 5 percent.

The last row of Table 5 provides an estimate of the difference in annual VMT for short-range Evs relative to long-range Evs. Not surprisingly, in all cases, EVs with short battery range are driven anywhere from 2,000 to 5,000 miles less than EVs with a high battery range, all results significant at the 1 percent level.

[13] While the NHTS datast does not report the range for vehicles, it reports make and model information, as answered by survey respondents. We estimate range based on this information for EVs using range data from fueleconomy.gov. We drop misclassified EVs and those with unknown make and model data.

**Table 5.** Electric Vehicle Driving Relative to Gasoline and Diesel-Powered Vehicles:
Household and Vehicle Controls
Control for Short-Range EVs

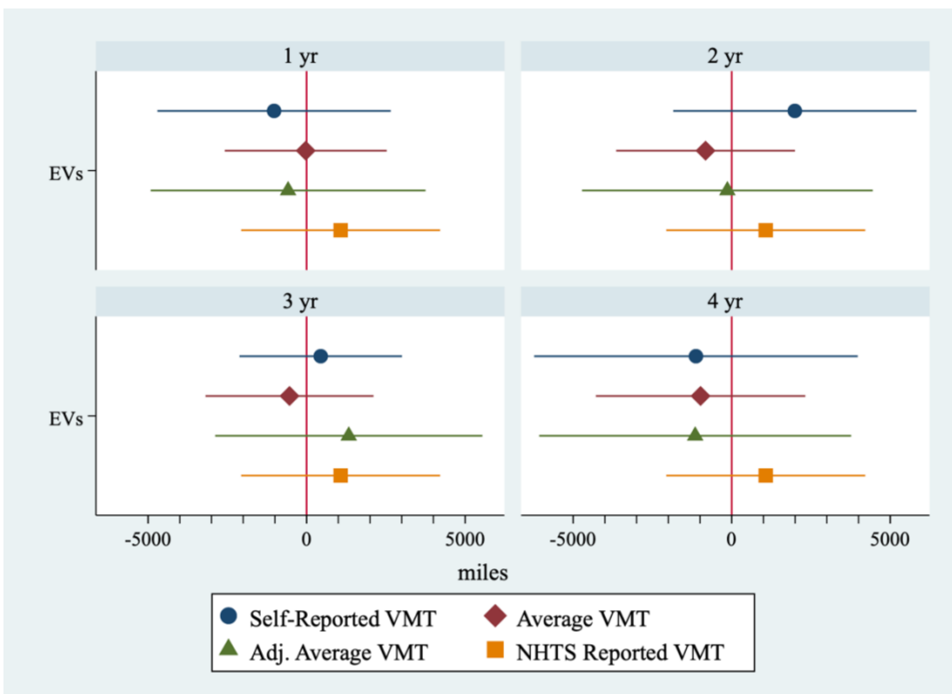
| Type of Electric Vehicle | (1) Self-Reported VMT | (2) Average VMT | (3) Adj. Average VMT | (4) NHTS Reported VMT |
|---|---|---|---|---|
| Plug-in Hybrid | -1,226*** | -1,956*** | -3,046*** | -669* |
| Long Range All-Electric | 37 | -1,010 | -78 | 1,802** |
| Hybrids | 2,542*** | 1,151*** | 2,169*** | 1,282*** |
| Short Range All-Electric | -3,296*** | -2,125*** | -4,442*** | -5,123*** |
| $R^2$ | 0.11 | 0.17 | 0.11 | 0.09 |
| Number of Observations | 62,873 | 69,790 | 69,778 | 79,626 |

Note: This table reports the difference in driving between the vehicles identified in the first column and gasoline or diesel operated vehicles. Each column reports a different measure of annual vehicle miles traveled. All estimates are calculated using sampling weights. The second row now captures only long-range EVs (Teslas). There are 436 EVs in the dataset, of which 113 are long-range, 247 are short-range and the range for 76 EVs is unknown or misclassified. We drop these 76 EVs for this regression.
The *p*-values are indicated by stars: *** p<0.01, ** p<0.05, * p<0.10

We must note that Teslas are the only long-range EVs in our data, so it is difficult to distinguish a Tesla effect separately from the range effect. Our controls for household characteristics, such as household income and location will capture some of the Tesla effect. Additionally, assuming that Teslas are preferred by environmentally conscious individuals that drive less, the Tesla effect would bias our result downward. These data may also capture many early adopters of Teslas, who are also likely to be drivers who drive less. Then, it is even more meaningful that despite a potential Tesla effect biasing our result downward, we find that long-range EVs are not necessarily driven less compared to gasoline or diesel vehicles.

Any statements about EVs using the 2017 NHTS are complicated by the fact that there are still few EVs in that data set. There are 436 EVs in our final data set, of which 113 are long-range, 247 are short-range, and the range is unknown or misclassified for 76 EVs. This is unsurprising since the data are based on surveys conducted in 2016, when there were fewer EV products and a sparser charging infrastructure relative to today. While there are still enough EVs for us to estimate results with statistical power, we would expect these results to only get better with a more recent round of the NHTS survey with more EVs, including non-Tesla long-range ones.

**Figure 1.** Difference in Driving Between Long-Range EVs and Gasoline/Diesel Vehicles By Year of Vehicle Age

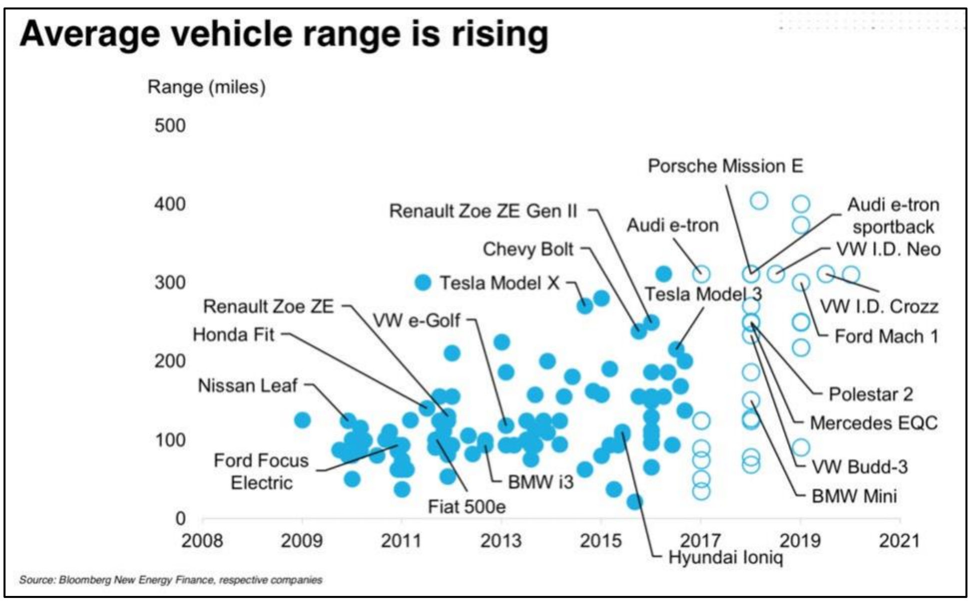



The NHTS adjustment for differences in driving as vehicles age may not reflect current driving and ownership practices. As a final check, we run regressions on sub-samples based on the vehicle age. Figure 1 graphs the coefficient estimates for long-range EVs relative to gasoline and diesel vehicles for vehicles that are one, two, three, and four years old. The bias from comparing newer EVs to older gasoline or diesel vehicles when measuring annual driving by average annual VMT should disappear when comparing vehicles of given age in each regression. Each of the four graphs in the figure plot the estimated difference in driving for long-range EVs compared to gasoline and diesel vehicles along with a 95 percent confidence interval. Given the smaller sample size, none of the estimates are statistically significant at the 95 percent level. But no matter what year is considered or which measure of annual VMT, the estimates are much smaller than suggested by the Davis analysis and, in many cases, suggest that long-range EVs are in fact driven more than gasoline or diesel vehicles.

**Policy Implications**

Once one accounts for battery range, the sharp difference in annual miles driven between EVs and gasoline and diesel-powered vehicles goes away for long-range EVs. With battery range increasing dramatically (see Figure 2),[14] focusing on longer-range EVs seems relevant for any research looking at the efficiency or distributional implications of policy to incentivize greater take-up of EVs. The distributional considerations are especially important for thinking about tax proposals for a VMT tax to replace in part or entirely the current motor vehicle fuel excise tax. Assuming that EVs are driven fewer miles than the vehicles they replace would bias such a revenue-neutral tax reform towards being more regressive, assuming EVs are disproportionately purchased by higher income households.

**Figure 2.** EV Vehicle Range Over Time




Source: Forbes (2018)

It is also important to remember that the 2017 NHTS dataset is based on sampling conducted in 2016, 6 years before this paper was written. The EV environment has experienced massive improvements in

[14] It is also reasonable to expect improvements in EV charging infrastructure going forward, which would improve VMT outcomes for EVs, although we don't focus on this in our analysis.

terms of technology, infrastructure, and adoption since then. If we see disappearing VMT differences using data from 6 years ago, we should expect to see much better outcomes today and moving forward. In the end, a definitive answer to the question of whether EVs are driven differently than gasoline and diesel powered vehicles may have to wait for the next release of the travel survey.

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## Appendix A: Notes and Comments on NHTS estimates of Vehicle Miles Traveled

### Estimating bestmile[15]

Bestmile is the NHTS's "best estimate of annual vehicle miles traveled (VMT)". We refer to this estimate as the "NHTS Reported VMT" through our paper. The Oak Ridge National Laboratory and Federal Highway Administration (henceforth jointly known as the NHTS agencies) estimate bestmile. Bestmile estimation incorporates several intermediate VMT measures and adjusts for vehicle age and other observed household and primary driver characteristics.[16] The NHTS agencies start with the odometer reading divided by vehicle age (what we call the Annual Average VMT and what Davis uses in his paper for analysis). NHTS agencies estimate the share of its lifetime miles traveled by an average car at each age using 2001 data. Then, they apply this relationship to the annual average VMT measure to estimate the annual mileage driven by the vehicle in its most recent year. This VMT measure extrapolating annual miles from the odometer reading through vehicle age is called "odommile."

From odommile, the NHTS agencies estimate bestmile by adjusting for other factors that daily driving is assumed to be a function of, namely the self-reported VMT (annmiles), characteristics of primary drivers, and other household characteristics and geographical attributes.[17] Depending on data availability, the NHTS agencies use one of seven approaches for estimating bestmile from these factors. Each approach estimates the relationship between the variables listed above (whichever are available) and VMT using 2001 data. For most of the approaches, NHTS agencies estimate separate models for three sets of grouos: 1) single vehicle households with one driver, 2) multi-driver households with an

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[15] We would like to thank Tim Reuscher, Layla Sun, and others at ORNL and related agencies that helped us understand bestmile estimation better through detailed correspondence.
[16] NHTS details its estimation of bestmile here: https://nhts.ornl.gov/assets/2017BESTMILE_Documentation.pdf
[17] The variables from NHTS that are used for this estimation are: annual self-reported VMT (annmiles), education level (educ), age class of the primary driver (R_AGEC), vehicle age class (VEHAGEC), vehicle type (VEHTYPE), area size (MSASIZE), census division (CENSUS_D), life cycle of the household (LIF_CYC), worker status (WORKER), gender of the primary driver (R_SEX), size of the household (HHSIZE), and driver to vehicle ratio (DRVEH)

equal number of vehicles and drivers, and 3) households with unequal numbers of vehicles and drivers. Note that bestmile VMT is computed only for automobiles, pickup trucks, vans, and sport utility vehicles.

The construction of BESTMILE also relies on estimation from the 2001 NHTS. That study relies on the measure, "ANNUALZD", which is an annualized estimate of two odometer readings that NHTS agencies have developed in the past.[18] The NHTS agencies apply this relationship between ANNUALZD and explanatory variables to 2017 data to estimate BESTMILE. The explanatory variables include ODOMMILES and self-reported VMT (ANNMILES). BESTMILE is thus a function of self-reported VMT, ODOMMILES (which is a function of annual average VMT), characteristics of primary drivers, household characteristics, and geographical attributes.

*Comparing the VMT estimates*

NHTS agencies have four measures of VMT estimates as we outlined above: 1) ANNMILES – self-reported VMT, 2) Annual average VMT estimated by dividing the odometer reading by vehicle age, 3) ODOMMILES – Annual average VMT adjusted for heterogenous driving behavior by vehicle age, and 4) BESTMILE – a VMT measure which is a function of odommiles, annmiles, characteristics of primary drivers, household characteristics, and geographical attributes. By definition, the NHTS agencies identify bestmile as the "best estimate" of VMT. While we generally agree with the NHTS classification, we compare the VMT measures below and note some issues with estimating bestmile, particularly with respect to EVs.

The annual average VMT is a crude measure of VMT, since it doesn't account for two important factors – 1) how much a vehicle is driven depends on its age and that vehicle age is in years whereas odometer reading is also sensitive to the number of months, especially for young vehicles (which EVs typically tend to be), and 2) the relationship between vehicle age and annual miles driven is not consistent over time. Odommile accounts for these differences. Accordingly, both annmiles and

[18] More details on ANNUALZD can be found in Appendix K in the 1995 NHTS user's guide

odommile correct for drawbacks of the annual average VMT measure. NHTS agencies prefer bestmile to odommile because “the odommiles calculation is subject to assumptions in driving patterns – mainly that driving of a given vehicle declines over time – which may lead to bias in the estimates.”[19] Bestmile attempts to fix this bias. Additionally, bestmile is preferred to annmiles since the latter may be more subjective and susceptible to the salience of driving miles to the survey respondent. On the other hand, bestmile is estimated based on observed data.

Going forward, it will be important that NHTS agencies estimate separate models for bestmile for EVs/PHEVs and other vehicles respectively. The current estimation, based on 2001 data, assumes that the relationship between determinants and VMT is similar across all vehicles. Accordingly, the 2017 bestmile is computed using the same model for ICEs and EVs. However, the relationships might not be as consistent across vehicles. The VMT for EVs might not decline at the same rate with age as it is estimated to decline for ICEs. It might even go up as charging stations become more prevalent and drivers become more familiar with locations of charging stations over time. Additionally, the relationship between other determinants and VMT might also be different for EVs. For example, location might play a stronger role in EV VMT than for ICE VMT. Since 2001 data had almost no EVs, it is fair that NHTS agencies used a general model to estimate VMT for EVs. However, moving forward, it might be better for NHTS agencies to estimate separate models by fuel type.

[19] NHTS bestmile documentation, pg. 11, available here: https://nhts.ornl.gov/assets/2017BESTMILE_Documentation.pdf.

**Appendix B. Bias Over Age In Proxying Annual Miles Driven With Average Annual Miles**

Assume annual miles driven in year $t$ is $M_t = MD^{t-1}$, where $D < 1$. This well approximates the quadratic mileage decline assumed by NHTS. For a vehicle that is $k$ years old, the average annual miles measure (dividing the odometer reading by vehicle age), is

$$\bar{M}_k = \frac{1}{k}(M_1 + M_2 + \cdots M_k).$$

The ratio of average annual miles to actual driving in year $k$ is

$$\psi_k \equiv \frac{\bar{M}_k}{M_k} = \frac{\frac{1}{k}(M_1 + M_2 + \cdots M_k)}{M_k} = \frac{1}{k}\left(\frac{M_1}{M_k} + \frac{M_2}{M_k} + \cdots + \frac{M_{k-1}}{M_k} + 1\right).$$

For any value of $k > 1$, we can show that $\psi_k > \psi_{k-1}$; in other words the upward bias from replacing actual miles driven in any given year $(M_k)$ by average annual miles $(\bar{M}_k)$ grows over time.

***Proof:*** Let $M_t = MD^{t-1} = MF^{1-t}$, where $F = D^{-1} > 1$.

$$\psi_k \equiv \frac{\bar{M}_k}{M_k} = \frac{\frac{1}{k}(M_1 + M_2 + \cdots M_k)}{M_k} = \frac{1}{k}\sum_{s=0}^{k-1} F^s = \frac{1}{k}\left(\frac{F^k - 1}{F - 1}\right).$$

Rewrite this as

$$\psi_k = \underbrace{\left(\frac{k-1}{k}\right)}_{\alpha}\left(\frac{1}{k-1}\left(\frac{F^{k-1} - 1}{F - 1}\right)\right) + \left(\frac{1}{k}\right)\left(\frac{F^k - F^{k-1}}{F - 1}\right)$$

or

$$\psi_k = \alpha(\psi_{k-1}) + (1 - \alpha)\left(F^{k-1}\right) > \psi_{k-1}$$

since $F^{k-1} > \psi_{k-1}$. This latter inequality holds since $\psi_{k-1}$ is an average over terms, each of which is less than $F^{k-1}$.

Since EVs tend to be newer than gasoline or diesel vehicles, using average annual miles rather than actual miles driven will lead to higher estimates of annual miles driven for older, gasoline and diesel vehicles than newer EVs.

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