How Regressive are Mobility-Related User Fees and Gas Taxes?

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Abstract

Economists have long recognized the efficiency properties of Pigouvian taxes to address environmental externalities and user fees for funding transportation infrastructure. A persistent concern with such policies is their distributional burden. The gasoline tax, which funds highways in the US, is widely viewed as regressive, and it is likely to become more so over times as higher-income households transition more rapidly than their lower-income counterparts to fuel-efficient or electric vehicles. This paper presents new evidence on the distributional burdens of the gasoline tax and other transportation-related user fees such as bus and light rail charges and a vehicle miles tax (VMT). While gasoline tax payments as a share of household income decline with income, this pattern is attenuated when these taxes are measured as a share of total expenditures. If the US were to switch from a gasoline tax to a household-level VMT, which would place a greater relative burden on hybrid and electric vehicles, the tax burden would increase, on average, for households in the top income and expenditure deciles. These better-off households would also bear much of the burden of an expanded commercial VMT, because they have larger budget shares devoted to expensive tradeable goods. User charges for airports, subways and commuter rail are progressive: low-income households use them less than middle- and upper-income households. Bus fees, in contrast, loom much larger for low- than high-income households.

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1 Introduction

Transportation decisions are replete with externalities such as carbon emissions, traffic congestion, and motor vehicle fatalities. Economists have long embraced user fees to address these externalities. Adam Smith (1776) wrote that user fee financing would promote efficient investment decisions, for if transportation infrastructure is "made and supported by the commerce which is carried on by means of them, they can be made only where that commerce requires them, and consequently where it is proper to make them." William Vickrey (1952) called for taxes and time-varying charges for subways to address congestion externalities, and Small, Winston and Evans (1989) were early advocates of a commercial Vehicle Miles Tax to charge truckers for the marginal damages they impose on roads. Yet Pigouvian mobility charges such as highway tolls and gas taxes remain politically unpopular. This may be due to their salience to those who use transportation infrastructure – Finkelstein (2011) suggests that raising such taxes is easier when they are collected by less visible means, such as electronic tolling – and to the belief that they are regressive.

This paper considers the distributional impact of various mobility-related user fees, including charges for airports, subways, commuter rail, and buses, as well as gasoline taxes and Vehicle Miles Taxes (VMTs). The analysis of these different strategies for funding infrastructure is particularly timely in light of recent policy developments. The Infrastructure Investment and Jobs Act of 2021 (IIJA) allocates grants for states and localities to build vehicle charging infrastructure, to replace or update public buses with low- or no-emission vehicles, and to explore options for electrification of commercial trucking at U.S. ports. In addition, as electric vehicles replace cars and light trucks powered by internal combustion engines, the VMT, which can be levied both on households and on commercial drivers, offers a way of avoiding a decline in the revenue source – gasoline taxes – that currently funds the Highway Trust Fund.

The rise of electric vehicles (EVs) has the potential to increase the regressivity of the gasoline tax. In the 1970s, fuel efficiency was achieved through lighter, lower performance automobiles and better-off households preferred gas guzzlers. Today, as EVs gain market share, the market penetration is much greater among households than others. Carmax (2017) reported that that 17 percent of hybrid/EV owners have household income of more than $200,000, and that 30 percent have incomes above $150,000. By comparison, the Congressional Budget Office (2020) reported that in 2017, only five percent of single-person households had incomes of

$179,100, and ten percent of two-person households had incomes of $182,800 or higher. High-income groups are those over-represented among EV buyers.

This paper begins by calculating the distribution of outlays on current user charges, such as public transportation user fees and the federal gasoline tax. We consider payments relative to income, as in Chernick and Reschovsky (1997), as well as relative to household expenditures, as in Poterba (1991). When household income is subject to transitory shocks, household expenditure may provide a more revealing measure of long-term well-being, and permanent income, than annual income. For households spending less than $30,000, outlays on gasoline account for close to 5 percent of total expenditures. The expenditure share falls below 2% among the highest-expenditure households. The current federal gasoline tax is regressive, though it is less regressive than it has been in the past.

The share of expenditure devoted to public transportation also declines with total expenditure over much of the distribution, although it rises at high levels as a result of commuter rail and air travel usage. Bus trip counts are much higher for low income individuals. Commuter rail and air travel usage increase with expenditure, and in areas with developed systems, subway trips are relatively independent of expenditure in those areas with developed systems.

A household-level VMT directly charges for road usage, and eliminates the implicit subsidy to hybrids and EVs under the current system. A household with two cars, each delivering 24 miles per gallon, that drives a total of 18,000 miles per year purchases 750 gallons of gasoline annually, with an 18.4 cent per gallon federal gasoline tax, and an average state gasoline tax of 26 cents per gallon, this household would pay $333 in gas taxes. Replacing both vehicles with EVs would save this annual outlay. Imposing a VMT would eliminate the implicit tax benefit given to electric vehicles (EVs); it would also charge drivers for their congestion externality, although setting the appropriate level of this Pigouvian tax is complicated. Because EV penetration in the US auto fleet at the moment is low, the distributional pattern of payments for a VMT that raises as much revenue as the current federal gasoline tax is very similar to that of the current gasoline tax. The two will diverge to a greater degree in the future, at least if current projections for EV adoption are realized.

We also consider a commercial VMT. Four states, Kentucky, New York, Oregon and-New Mexico, have already adopted such taxes. Under the assumption that trucking costs are fully passed through to consumers of tradeable goods, and that VMT charges are added to trucking costs, the impact of a VMT on a given household depends on its budget share for tradeable goods. These are the goods that require transportation. We find that higher income households face greater burdens from the commercial VMT than their lower income counterparts, because tradeable goods represent a larger share of their budget.

This paper builds on a long literature on the distributional impacts of Pigouvian taxes related to transportation services. Metcalf (1999) noted that environmental taxes meant to mitigate the social damage of pollution tend to be regressive. Another paper by Metcalf (2022) is closely related to this study. It presents a detailed analysis of the distributional impact of the VMT versus a gasoline tax. In projecting the growth of EVs in the vehicle fleet, and in comparing households at different points in the income distribution, there are some differences in approach in the two studies; we highlight them below. The overall conclusions are very similar, however. Other related research includes Levinson (2019), which notes the relative regressivity of regulating fuel efficiency and imposing fuel taxes. Davis and Sallee (2020), Langer, Maheshri and Winston (2017), and van Dender (2019) all study the VMT. Weatherford (2012) finds that moving from a gasoline tax to a VMT will have little distributional impact. Our analysis does not consider the distributional effects of transportation related externalities, which Banzhaf, Ma and Timmins (2019) find to place disproportionate burdens, through pollution, on low-income households.

The remainder of this paper is divided into five sections. The next section provides background information on transportation-related user fees, including their level and their role in federal, state, and local budgets. Section 3 introduces the two data sets, the Consumer Expenditure Survey (CEX) and the National Household Travel Survey (NHTS), that that form the basis for our analysis. Section 4 presents our core findings on the distributional impacts of current transportation user fees. Section 5 focuses on the household and commercial VMT taxes, and compares their distributional burdens to the current gasoline tax. There is a brief conclusion.

2 Background on Transportation-Related User Fees

Federal, state, and local governments all devote substantial expenditures to transportation infrastructure. The federal government spends little on public transportation directly, relying more on intergovernmental grants. State and local governments both make direct outlays on transportation. Transportation infrastructure is funded through a combination of user fees and general government resources. User fees can refer to direct charges, such as tolls to access a bridge or highway, or to gasoline taxes. When purchasing an airline ticket, for example, a consumer will pay a variety of user fees to different government entities, including taxes or fees to the Federal Aviation Administration (FAA), the Environmental Protection Agency (EPA), the Department of Homeland Security (DHS), and the local airport.

Transportation-related user fees do not contribute a large share of total revenues for any level of government. Most local and state governments rely heavily on intergovernmental transfer to fund infrastructure. Since the 1990s, local governments have increasingly relied on user fees to fund airports and public transportation more generally. States have generally become less reliant on car-related fees over time, as fuel taxes fell from an average of 10 percent of state budgets in 1970 to three percent of state budgets in 2017. Federal revenues rely very little on any form of transportation user fee. Fuel taxes comprise a declining share of Federal revenues, as nominal tax rates have been kept constant since 1993 and fuel efficiency has increased.

The gap between transportation-related revenues and expenditures has generated interest in new funding sources. The Infrastructure Investment and Jobs Act of 2021 proposes new programs and pilots around VMT fees, but political acceptance of such taxes will depend, in part, on their cost to different subsets of the population. We now examine the distributional consequences of current transportation-related user fees and potential VMT alternatives.

3 Data

Our household travel analysis draws on two primary datasets. One is the National Household Travel Survey (NHTS), which we use to study transportation utilization by mode, vehicle characteristic, and driving behavior, by households' expenditure group. The NHTS is conducted every 8 years to study household travel patterns, and is a key input into national, state, and regional infrastructure planning. The survey recruits households and asks them about their trips in a 24 hour period, including mode, purpose, trip length, time of day, among other characteristics. These surveys are then linked to a suite of demographic and socio-economic, vehicle, and location characteristics. We use data from three 2017 NHTS products: the household survey, the trip level survey, and the vehicle survey. This survey covers roughly 139,000 households who use 256,000 distinct vehicles and make nearly 925,000 trips on the survey date. The data are collected at the person-level, and then aggregated to households. The survey also provides weights used to aggregate households to population level statistics. We use this data set to estimate the number of households in various expenditure ranges who are using each mode of transportation, to calculate their driving behavior, and examine vehicle characteristics. To assess alternatives to the current policy regime, we modify this 2017 NHTS dataset, with more details in Section 5.

We use the trip level data to study trip shares by mode and expenditure. We focus on private vehicle, bus, subway, commuter rail, and airplane. The NHTS also includes data on the vehicles owned by each household, including their age, fuel type, and annual miles traveled. The NHTS has information on travel mode utilization, but not on travel expenditure, or total expenditures. For that, we turn to a second data source: the CEX. It is a nationwide survey conducted quarterly by the Bureau of Labor Statistics. It provides estimates of annual expenditures on a variety of consumer goods and services, as well as total household expenditure and income. Expenditures and income are nominal in the CEX data, so we convert to real 2017 dollars to keep incomes comparable to the most recent NHTS data. Appendix Table 4 shows that we are able to nearly match public reports using the public use microdata.[1]

In order to calculate how many gallons of gasoline households have purchased, and the taxes paid on them, we complement the CEX sample with annual data on state gasoline prices and taxes. State motor fuels tax rates data come from the Brookings-Urban Tax Policy Center. Our focus is on the total gasoline user fee levied in each state in each year. To estimate fuel costs per gallon, we use the "all grades all formulations" retail price average for gasoline as reported by the Energy Information Administration (EIA), 2000-2021. The EIA reports annual data for nine states. For the other 41 states and Washington, D.C. we map states to one of seven regions assigned by the EIA.

For the commercial analysis, we incorporate data from the Bureau of Economic Analysis' (BEA) Total Requirements tables, specifically the "Industry by Commodity/After Redefinitions/Producer Value" table for 2012, the most recent data available. These tables provide an estimate of the amount of input industry is required, in dollars, to produce one dollar worth of commodity output. We focus on the total requirements in trucking transportation to

[1] Specifically, we replicate the Consumer Expenditure Survey Table 1203.

produce a suite of consumer commodities listed in the CEX Table 1203.[2] For a crosswalk, see Appendix Table 9.

4 Distributional Impact of Charges for Public Transportation

To measure the distributional burden of user fees for public transportation, we compute the share of total expenditure devoted to public transportation, and then rank households to deciles based on their total expenditures. Especially for those at the highest and lowest income levels, expenditure may be a more meaningful indicator of household well-being than expenditure. Figure 1 shows the ratio of expenditures to income in CEX, by either income deciles or expenditure deciles.

[Insert Figure 1]

Panel (a) shows that at low income levels, income is often lower than expenditures due to net transfers from tax credits or in-kind aid. At high incomes, expenditure falls below income because of substantial saving and because of transitory income such as capital gains from selling a house. Appendix Table 5 emphasizes that a household's expenditure decile and its income decile, while correlated, need not coincide.

If we instead reorder households by their expenditure decile, we see that across all deciles, the ratio of expenditure to income is much flatter and closer to 1. This hews closer to what we would expect from a permanent income model. When we do not have expenditure data for specific travel modes, as in using the NHTS data, we report utilization rates for various transportation services. Because our analysis orders households by total expenditure, we must predict household expenditure in the NHTS datasets, which only provides income ranges. Appendix A outlines how we use demographic, socioeconomic, graphical and temporal information in the CEX to predict expenditure levels in the NHTS.

4.1 Public Transportation

Public transportation modes differ greatly in ease of access, wait times, and cost. Better-off households may find easier to adjust than their poorer counterparts. Figure 2 breaks down the number of trips taken each day per household, by mode and expenditure decile, using data from the NHTS. For each income group, we plot the share of trips taken by either bus, subway,

[2] For a breakdown of consumers' expenditure groups, please refer to https://www.bls.gov/cex/tables/calendar-year/mean-item-share-average-standard-error/cu-income-before-taxes-2019.pdf

commuter rail, or air travel. We plot two bars, the lighter bars indicate major public transit cities, defined as those with at least 10% of the population commuting by public transit: New York City, Chicago, Washington, DC, Boston, Philadelphia and San Francisco. The darker bars represent travel behavior in all of the other major metro areas in the NHTS, as well as those households living in sub-metro areas.

[Insert Figure 2]

Panel (a) shows that bus utilization is decreasing in expenditure, with households in the lowest expenditure decile using the bus approximately 0.2-0.7 times each day (roughly once every one to three days). In contrast, individuals in the highest expenditure decile use the bus only 0.05-0.12 times a day. Panel (b) shows the same breakdown for subway use. Subway use is very popular for all expenditure deciles in major public transit cities. In contrast to bus usage, subway use increases with expenditure. This reflects the reliance of low-income inner city neighborhoods on public transit, as well as the relatively high incomes in urban cores across the country, such as Manhattan, where proximity to a subway is highly valued. Commuter rail use, in panel (c) displays the most progressive use of any form of land-based public transit. The highest expenditure survey respondents in major public transit cities reported using commuter rail 0.17 times each day, while utilization falls steeply for those in the bottom 7 expenditure deciles. Commuter rail tends to be co-located with wealthy suburbs surrounding dense cities, and fare costs are higher than public bus or subways. Finally, panel (d) shows air travel by expenditure decile. The gap between public transit cities and all other areas closes significantly, as airports are located in all city types. Air travel is highly progressive, with the highest expenditure decile taking more than 22 times as many trips as those in the lowest deciles; the highest expenditure bin households take air travel on average about 15 days per year, while the lowest expenditure decile taking a flight only once every 15 months or so.

These utilization breakdowns reflect households' decisions based on the total costs of accessing infrastructure. Households pay user fees, which contribute to revenues collected by infrastructure providers, but they also pay in time costs, as well as in other ways such as locations rents. Observing the user fees alone, even for the largest public transit authorities, household user fees come nowhere near funding infrastructure operating expenses.

[Insert Figure 3]

Figure 3 plots the average fare to average operating cost (exclusive of capital costs) ratio for the top 50 largest public transit authorities. The average authority recovers only 40% of the cost of providing a trip, reflecting large funding gaps from user fees alone.

4.2 Private Vehicles

We use CEX data to calculate gasoline expenditure relative to total expenditure. Figure 4 presents data on the distribution of gasoline expenditure shares, as well as federal gasoline tax expenditure shares. In order to calculate expenditure on taxes, we need to know how many gallons each household uses. We bring in data on annual average retail gasoline prices from the EIA by state or region, and divide total expenditure by price per gallon, inclusive of taxes. We then multiply the imputed number of gallons by the state and federal taxes reported that year from the Tax Policy Center data.

[Insert Figure 4]

Panel (a) in Figure 4 shows that households' annual expenditure on gasoline in 2017 was roughly the same as it was in 2001, after peaking in 2009 prior to the fracking boom. We also see that the highest expenditure ventile households spend less than half the share on gasoline as do the households in the lowest ventiles. Panel (b) shows that average federal fuel tax expenditure shares declined markedly between 2000 and 2010, as inflation and improvements in fuel efficiency eroded the burden of the federal gas tax. Expenditures on gasoline taxes at lower incomes are lower as a share of income in 2017, relative to those of better-off households, than in 2000. This is the result of greater gasoline expenditures, in total, at higher expenditures. This may be the result of better-off households driving more miles, or of their driving more gas-hungry luxury cars or SUV's, which took off in the mid-2000s in the US.

Appendix Figure 10 shows the pattern of gasoline tax expenditure relative to household income, and ranks households by income; it also suggests that the distribution of fuel taxes has become more progressive over time. The reduction in regressivity over time seems to be driven be lower expenditure shares among low-income households, while higher income households pay similar shares to what they did in 2001. Appendix Figure 11 shows the same analysis for state fuel taxes, either by income share or expenditure share. While the burden of taxation has fallen for most expenditure levels, the upper end of the distribution masks important heterogeneity in vehicle trends. On the one hand, higher income individuals drive more miles, pushing their expenditure share higher. On the other hand, they tend to own newer vehicles, which tend to have higher fuel standards, shown in Appendix Figure 12.

An important modern trend motivating this paper is that higher income households also adopt hybrid and electric vehicles at much higher rates than their low-income peers, as show in Figure 5(a). Additionally, the richest households have vehicles that have higher fuel efficiency standards, reflected in Figure 5(b).

[Insert Figure 5]

Figure 5 presents an important change in the composition of vehicles owned by the highest income households, many of which are also high expenditure. The National Personal Travel Survey from 1977 found that higher income households owned *less* fuel efficient vehicles, on average their cars ran 3 fewer miles per gallon.[3] The most recent reports from the 2017 National Household Travel Survey, in Figure 5 panel (b), show that this relationship has flipped as richer households buy hybrid and electric vehicles, which often have higher up-front costs than gasoline powered cars. As of 2017, the highest income households own vehicles that run, on average, 1.5 more miles per gallon. This change means that higher income households pay less in fuel taxes to travel the same distance as poorer households.

We show in Appendix B how the progressivity of gas taxes and carbon fees depends on the nature of the abatement technology. When better gas mileage meant reducing car weight and power, then the poor were more likely to take advantage of that possibility. Consequently, in the 1970's, gas taxes were paid disproportionately by the rich driving heavy cars. When better mileage means buying a Tesla, then gas taxes become a disproportionate burden on the poor, who cannot afford the upfront cost of green technology.

5 Distributional Impact of Alternative User Fee Structures

This section applies the same approach to computing the distributional impact of user fee structures to two alternatives to the status quo, personal and commercial VMTs.

5.1 Comparing the Federal Gasoline Tax to a VMT

First, we consider replacing the federal gasoline tax with a VMT levied on households. We envision limiting this to personal vehicles, as much of the commercial vehicle fleet relies on

[3] The NPTS, like the NHTS, only provides reports based on income, so we are unable to compare vehicle characteristics by expenditure across the two datasets.

diesel. The federal gasoline tax was last updated in 1993, when it was set at 18.4 cents per gallon. To keep up with inflation, the equivalent tax rate in 2021 would be set at about 34 cents per gallon. Further diminishing the purchasing power of the gas tax, infrastructure costs have been increasing, in particular for new lane-miles, as reported by Brooks and Liscow (2019) and Mehrotra, Turner and Uribe (2021). Finally, vehicles have become more fuel efficient, and the tax collected per vehicle mile traveled has fallen. The static tax rate, rising infrastructure costs, and increased fuel efficiency have all contributed to a growing gap between tax revenues allocated to the Federal Highway Trust, $43.4 billion in 2021, and its expected outlays, expected to average $60.4 billion over FY2021-FY2025 (Kirk and Mallett, 2020).

US residents are increasingly adopting hybrid and electric vehicles, whittling away at the gas tax revenues. As of 2020, sales of hybrids, plug-in hybrids, and all-electric vehicles grew to 5.4% of all light vehicle sales, from 2.3% in 2011, the year in which all-electric vehicles first came to market, and 0% in 1999, the year the Toyota Prius came to market. Importantly, all-electric vehicle sales alone have grown from 0.1% of all sales in 2011, to 1.7% in 2020, none of which pay any federal gas tax (Davis and Boundy, 2019). As this market continues to grow, policymakers have increasingly considered switching to the vehicle miles tax (VMT), which would tax drivers based on their road usage rather than gas consumption, ensuring that electric car drivers would contribute to paying for the infrastructure maintenance costs that they impose on the system.

Proposals for updating the gasoline tax or adopting a VMT vary, so we consider three alternative scenarios: (1) anchoring the VMT's tax per mile to the mean effective tax per mile under the current federal gasoline tax rate, (2) adjusting the federal gasoline tax such that it will fully fund the federal Highway Trust Fund (HTF) outlays expected over 2021-2025, and (3) setting the VMT tax per mile to fully fund the HTF outlays expected over 2021-2025. We detail each of these options below, but first outline some characteristics of the current tax regime, including miles traveled, mean revenues paid per person, and aggregate revenues.

5.1.1 Miles and Federal Revenues under Current Gas Tax

As of 2017, the most recent year for while we have data from the National Household Travel Survey, the average household drives about 12,000 miles per year, or about 33 miles per day. This mean masks substantial heterogeneity in travel, with the 25th percentile driving 15 miles per day, and the 75th percentile driving nearly triple that at 42 miles per day. Additionally, the dark bars of panel (a) in Figure 6 shows that higher expenditure households tend to drive more per annum than their low-expenditure counterparts, suggesting the gasoline tax would be progressive. However, for taxes paid per mile, we need to know not only how many miles households drive, but how many miles per gallon each vehicle uses, and on average, lower-expenditure households drive older and less fuel efficient vehicles. The first column in Table 2 shows that lower expenditure households pay less in annual gasoline taxes than their higher expenditure counterparts. However, the highest expenditure households are much more likely to have fuel efficient hybrid or electric vehicles, reducing their tax burdens to even lower than the lowest expenditure decile gasoline households.

5.1.2 Modeling the Effects of a Change in Per-Mile Travel Costs

To analyze the impact of various alternatives to the current user fee structure on gasoline consumption, we develop a simple theoretical framework. Let each household i have a quasi-linear separable utility with power function for transport such that,

$$U_i(T_i) = Y_i - pT_i + AT_i^{\sigma} \tag{1}$$

Households earn income Y_i, and T_i represents travel in miles, which is paid at a price per mile, p. This yields a first order condition of the constant elasticity functional form after taking logs,

$$\frac{\partial U_i}{\partial T_i}: ln(T_i) = \frac{1}{1-\sigma} ln(A\sigma) - \frac{1}{1-\sigma} ln(p) \tag{2}$$

Equation 2 identifies the price elasticity of demand for travel, $\varepsilon_g = -\frac{1}{1-\sigma}$, which we set to $\varepsilon_g = -0.31$, a middle ground in the elasticities estimated by Levin, Lewis and Wolak (2017).

Each of our three options will use a different $t_j \in \{t_1, t_2, t_3\}$, and since each option would replace the existing fuel tax, the price paid after adoption is the original gas price per mile paid at the pump, p, less the original gas tax per mile, τ, plus the proposed tax per mile, t_j, either a VMT or an updated gasoline tax.

In reality, initial p and τ are going to vary by the observed gasoline prices in one's area, as well as by a household's fuel utilization, such that each household has their own gas price per mile, p_i, and their own tax per mile, τ_i,. Moving from a tax on gasoline consumption, to a tax on miles consumption, removes the heterogeneity in how much people are taxed per mile, so t_j is fixed across households for VMT proposals.

For hybrid and electric vehicles, we have to modify their price per mile, as they do not pay the federal fuel tax as gasoline vehicles do. To do this, we set the cost per mile, p^e, for electric vehicles at 4 cents, which assumes the vehicle travels 3 miles per kWh, at the average rate for electricity of 11.7 cents per kWh (Advanced Vehicles Testing Activity, 2011). For hybrid vehicles, we assume an average price of $2.41/gallon, taken from the NHTS sample, and an efficiency of 45 mpg, yielding a hybrid cost per mile of p^h = $0.055, or 5 and a half cents per mile. These prices do not vary across households due to data limitations.

We can calculate miles driven under t_j as the initial miles driven, T_i, less (plus) the change in miles as prices rise (fall), relative to the initial price per mile,

$$T_i^{(j)} = T_i + T_i \left(\frac{t_{j-} \tau_i}{p_i}\right) \varepsilon_g \tag{3}$$

and tax revenues are $t_j \times T_i^{(j)}$. We consider the distributional impact of three policy options, corresponding to our three different revenue scenarios, which differ only in their proposed t_j.

Before considering alternative policies, since this paper has been motivated by the increasing share of high-expenditure households adopting electric vehicles, we construct a counterfactual world that captures not today's EV penetration in the marketplace, but a scenario that corresponds to some years into the future. Specifically, we allow for sales of hybrid and electric vehicles (HEV together, HV and EV for hybrid and electric vehcles, respectively), to continue to grow over the next fifteen years, and track how this translates into compositional shifts in the stock of vehicles in the personal fleet. We assume that by 2037, approximately one third of the vehicle fleet will be HEV, and use this counterfactual composition to compare the distribution of the gasoline tax and a VMT. Appendix C provides details on how we construct the counterfactual vehicle fleet for 2037.

5.1.3 Policy Counterfactuals

(1) Match VMT at Current Effective Tax/Mile: Our first VMT option would set $t_1 = \frac{1}{n}\sum_i \tau_i = \$0.0089$, roughly 9/10ths of a cent per mile. This policy would induce no behavior changes on average; however, depending on the difference between t_1 and τ_i, it would still induce a change in miles driven for individuals.

(2) Fully Fund the HTF with a Gasoline Tax: Our second policy counterfactual would raise the federal gas tax, t_2, to fund the HTF. Of the $40.5 billion raised to fund the FHT 2017, federal fuel taxes comprised $25.7 billion, or 64% of the revenues. Over the 2021-2025 fiscal years, projections estimate FHT outlays of $60.43 billion on average, with revenues coming up short at only $42.9 billion.[4] We set the gasoline tax such that

$$\$60.43\ billion = \sum_{i \in gas} t_2 T_i^{(2)} \tag{4}$$

We minimize the difference between the budget target and gasoline tax revenues to estimate a t_2 = $0.0323 per mile, or $0.727 per gallon. Importantly, this tax is leveied only on the subset of households driving gasoline powered vehicles in 2037.

(3) Fully Fund the HTF with a VMT: Finally, we set t_3 to fully fund the HTF, using a VMT.

$$\$60.43\ billion = \sum_{i} t_3 T_i^{(3)} \tag{5}$$

We minimize the difference between this budget target and VMT tax revenues, yielding a VMT of t_3 = $0.026. This is roughly 20% lower than the gasoline tax in proposal 2, as the wider tax base allows more people to contribute less per mile.

[Insert Table 1]

Table 1 summarizes the taxes per gallon, and taxes per mile under the current baseline, as well as the three policy counterfactuals.

5.1.4 Counterfactual Results

Figure 6 shows the distributional results of adopting a VMT meant to match the average current gasoline tax per mile. Panel (a) shows that driving patterns remain roughly the same, no matter the expenditure decile, across the baseline tax and proposed VMT. Panel (b) plots the average taxes paid under both schemes, by expenditure decile. On average, households in the bottom seven expenditure deciles end up paying lower taxes per year under the VMT than under the gasoline tax while those in the top three expenditure deciles pay more. This is driven by the small share of HEV's, roughly 2.5% of the current stock, landing mostly in the top 40% of the expenditure distribution, with 75% of all HEV's in the these expenditure deciles.

[Insert Figure 6]

Figure 7 plot the miles driven and annual taxes paid by expenditure decile for the 2nd and 3rd proposals, in which we use the 2037 counterfactual vehicle composition and fully fund the HTF. Panel (a) compares the miles driven under the gasoline tax and the VMT. Miles driven

[4] Currently, these shortfalls are paid from general revenues. If general revenues come from income taxes, these contributions are quite progressive, with high expenditure households paying large amounts in income taxes, as in Appendix Figure 13. However, if these general revenues are financed through debt, there is less concurrence on the progressivity of the debt burden on households.

under the two scenarios are nearly identical until the fifth expenditure decile, after which miles driven under the gasoline tax begin to outstrip the miles driven under the VMT, for a mileage gap of almost 4000 miles in the highest expenditure decile. This wedge is driven by the behavioral response of HEV households, which are concentrated in the highest expenditure deciles, responding to a large increase in their per-mile costs, as they had previously paid no fuel taxes.

[Insert Figure 7]

Panel (b) of Figure 7 translates miles driven to taxes collected, based on the individual vehicle's fuel efficiency in the case of the gasoline tax. Households in the first through sixth expenditure deciles pay significantly higher taxes under the gasoline tax scheme than under the VMT scheme, reflecting the higher share of less-efficient gasoline vehicles among these households, as well as relatively few miles traveled. At the seventh expenditure decile, households pay roughly equal taxes under both schemes, while the top three expenditure deciles pay considerably more under the VMT scheme than the gasoline tax. We forecast that about 55% of the vehicle fleet in the top 3 deciles will be HEV by 2037, while only 21% will be HEV in the bottom seven expenditure deciles, driving these gasoline-VMT tax payment wedges.

We also explore average taxes paid by vehicle type (gasoline, hybrid, electric), for our 2037 VMT policy counterfactual, and examine how driving behavior responds to the tax policy. Table 2 shows the annual average taxes paid per household, by expenditure decile and vehicle type. We present payments under the 2017 composition and baseline taxes, the 2037 VMT proposal without allowing for the behavioral response outlined in 5.1.2, and the full model under the 2037 VMT proposal.

[Insert Table 2]

Under the current tax policy, hybrid and electric vehicles pay significantly less or even no gasoline tax relative to households with gasoline vehicles. Comparing the second and third columns, we see that for gasoline vehicles, the increase in per mile costs under the 2037 VMT induce a 5% decline in revenues, as drivers adjust their mileage downwards. In contrast, for the group with the largest increase in per mile costs, the electric vehicle owners, they would pay around 12% higher taxes if we did not allow for driving behavior to respond to the per-mile price increase.

None of these calculations include the potential benefits of reducing other taxes that are currently levied to fund the HTF, or the lower driving externalities, such as reduced congestion and emissions, that might be associated with higher taxes. We note that a VMT would not be levied at the gas pump, but rather might be paid in a few installments each year. This could affect price salience and might change the value of ε_g we have assumed in this analysis.

5.2 Expanding the Commercial VMT

We also consider the implications of an expanded vehicle miles tax for commercial vehicles. Heavy trucks are currently taxed at $0.24 per gallon of diesel, but this taxation is unlinked to the value, weight, or distance of the shipped goods. This results in trucks often maximizing their load capacity, which can result in significant road damage. In most states, the majority of trucking taxes paid are fuel taxes, registration fees, and tire taxes. Small, Winston and Evans (1989) note that in a handful of states, taxes have varied by miles traveled or by vehicle weight. New Mexico, New York and Oregon have moved towards a VMT for commercial trucks that varies with the trucks' maximum load capacity ($0.01-0.29 per mile, depends on weight). On the other hand, Kentucky has adopted a flat fare structure set in the middle of the other states' ranges at $0.03/mile, regardless of weight.

Our analysis of the commercial VMT differs from that of the personal driver VMT in two ways. First, we do not replace the diesel tax with a VMT, but instead add a VMT in addition to the diesel tax, as the commercial vehicle fleet is not greening at the same rate as the personal fleet. Second, in addition to analyzing how a VMT would change commercial vehicles mileage (to be added in next draft), we analyze how adopting a commercial VMT changes the end-user price of traded goods. This unifies our analysis of the commercial and personal VMT policies by centering both of them on the household, rather than the vehicle. In the commercial context, we first estimate the share of shipping costs and fuel taxes in household expenditure. Next, we explore how an additional commercial VMT would impact household's expenditure and consumption bundles.

5.2.1 Current Indirect Federal Diesel Tax Burdens on Households

We first calculate the share of consumer expenditures attributable to shipping costs, in particular those from commercial trucking, and federal diesel taxes. To do so, we use data from the BEA's Total Requirements, input-output tables, which tell us how many dollars of trucking transportation costs are needed to produce a dollar of various output commodities. The total requirements tables list inputs and outputs by industry code, NAICS, or by commodity code, but these are not available in the CEX, so we crosswalk commodities and CEX expenditure categories by hand. Appendix Table 9 provides a detailed crosswalk; when categories are more granular in the input-output tables than in the CEX, we average the trucking costs within the CEX category, across input-output commodities. Across all CEX categories, we find that truck transportation contributes to about 0.72 cents for every dollar of output, but this varies from 0.04 cents (rented dwellings), to 3.1 cents (water and other public utilities) per dollar of final output. Trucking contributes to 0.8% of GDP, so we adjust our trucking shares upward to match this on average, which means inflating them by about 10% (Bureau of Transportation Statistics, 2018).

The input-output data give us the truck transportation share of final output, so to calculate the share of household expenditure going to diesel taxes, we include statistics from the American Transportation Research Institute, who find that that marginal cost of a mile of trucking is about \$1.646 (Leslie and Murray, 2021). Given a federal diesel tax of \$0.24/gallon, and a mean fuel efficiency of 6.4 miles/gallon, this translates to diesel costs of \$0.038/mile, or about 2.3% of the marginal mile cost. With these data in hand, we can calculate the diesel tax burdens for each household's final consumption bundle,

$$e_i^{diesel} = 0.023 \times \sum_c e_{ic} \times \gamma_c \tag{6}$$

where e_i^{diesel} is the household expenditure on diesel taxes, e_{ic} is household i's expenditure on commodity *c* reported in the CEX, and γ_c is the trucking input needed to produce one dollar of final commodity *c.* Total expenditure on trucking is the sum, over all commodities in a household's consumption bundle, of each commodity's trucking share multiplied by expenditure on that commodity. To deflate this to money spent on diesel taxes, we multiple trucking expenditure by the 2.3% share that diesel taxes contribute to the total trucking cost.

[Insert Figure 8]

Figure 8 shows the distribution of average diesel tax shares and diesel taxes paid by expenditure decile. As panel (a) shows, the total share of diesel taxes in the average household's expenditures is low, ranging from 0.015% of total expenditure for the lowest decile, to 0.011% for the highest expenditure decile. Diesel tax shares are regressive in shape, as the expenditure shares fall monotonically by decile, but they add up to fairly minimal amounts. Panel (b) shows that the lowest expenditure decile can expect to contribute about \$2 per year indirectly to federal diesel taxes, while the highest expenditure households contribute, on average, about $19 per year.

5.2.2 Implications of Commercial VMT Adoption

Setting the VMT on commercial vehicles could be informed by the costs imposed by truckers on pavement and bridge maintenance. Beider and Austin (2019) report estimates social costs imposed by heavy trucks per mile. Costs increase with vehicle weight, holding axles fixed: for example, for 5-axle trucks, the damage costs per mile are estimated to increase from $0.05/mile for 70-80k lb. truck, to $0.85/mile for 110-120k lb. truck. Costs also decrease with vehicle axle count: a truck weighing 100-110k with 5 axles imposes $0.83/mile of damage, while an additional axle drops this damage to $0.50/mile. Unfortunately, these damage costs are significantly higher than any VMT adopted, be it flat or varying by weight. As such, we anchor our analysis to a simple flat VMT, as in Kentucky, and set to $0.03 per mile. Combined with the existing diesel fuel tax cost per mile, this nearly doubles the taxation costs per mile, increasing them from $0.038 to $0.068. We choose to supplement rather than supplant as the electrification of the commercial vehicle fleet lags that of the personal vehicle fleet, with the overwhelming majority of commercial drivers still pay diesel taxes.

In order to analyze the impact of adopting a commercial VMT, we calculate the change in expenditures needed to purchase a household's original consumption bundle, demonstrating how much expenditures must grow to keep people at their original bundles. These constructs are similar to the concept of compensating variation; however, we have abstracted away from utility functions and income.

Final expenditure on any item can be decomposed into expenditure on the good, and the expenditure on the diesel tax component necessary to ship the good to the purchaser. As such, households, indexed by *i,*spend a portion, $1 - \alpha_c^t$, of their total expenditures on consumption goods, $good_{ic}^t$, and the diesel taxes levied on said goods, tax_{ic}^t:

$$e_{ic}^t = (1 - \alpha_c^t)e_{ic}^t + \alpha_c^t e_{ic}^t \tag{7}$$

$$e_{ic}^t = good_{ic}^t + tax_{ic}^t \tag{8}$$

c indexes commodities, and the shares are anchored to the total requirements. After a tax policy change, we calculate expenditure responses, holding the household's original consumption bundle fixed in time 0:

$$\Delta e_{ic} = \left(\frac{1-\alpha_c^0}{1-\alpha_c^1} - 1\right) e_{ic}^0 \tag{9}$$

Figure 9 displays the results of adopting the proposed commercial VMT. At the lowest expenditure decile, total expenditure needs to increase by 0.0138% in order to accommodate the near doubling of the commercial diesel tax per mile. This declines to 0.0131% for the middle expenditure deciles, before rising again to 0.0135% for the top deciles. This increases the out of pocket costs for the lowest deciles from $2 to $4 per year, while the highest decile see indirect diesel tax payment rise to $36, from $19.

[Insert Figure 9]

Overall, a significant increase in the commercial per mile tax results in small changes in out of pocket contributions, especially relative to adopting a personal VMT. Table 3 summarizes the estimated revenue yield as well as the distributional outcomes for each of the policy counterfactuals we have considered. Extrapolating the vehicle fleet forward in time, if we were to fully fund the HTF with user fees, structuring those fees as a gas tax puts the lowest relative burden on the highest spending households. Annual out of pocket costs increase from $364 at the low end before peaking for the seventh expenditure decile at $713, before falling nearly 30% for the highest spending households to $504. A VMT better expands the tax base by charging per mile, rather than fuel, as higher expenditure households increasingly opt for highly efficient HEVs; tax burdens increase nearly monotonically, only dropping marginally for the highest decile as the 10th decile has a higher share of electric vehicles than hybrid vehicles, relative to the 9th decile. Finally, the impact of levying a commercial VMT, even assuming full passthrough of the tax onto the final cost of goods, only moderately increases households' tax burdens, on average increasing indirect diesel tax burdens from $7.66 to $13.94 per year.

[Insert Table 3]

6 Conclusion

Changing patterns of vehicle ownership in the last few decades have contributed to a shift in the distributional burden of the gasoline tax, and prospective changes will amplify these changes. In the late 1970s, the miles per gallon for vehicles owned by high income households were lower, on average, than those for low-income households. As electric vehicles and hybrids have become more common, and as the fuel efficiency of new vehicles has increased, this pattern has shifted: in 2019, vehicles driven by high-income households were on average more fuel efficient than those of low-income households. These changes mean that policymakers must grapple with potentially rising inequity in who bears the burden of the fuel tax.

In this paper, we examine the impact of replacing the gasoline tax with a VMT levied on all drivers, or one levied only on commercial vehicles, as a way to bolster declining revenues from gasoline and diesel taxes. We find that adoption of these policies would result in a less regressive user fee burden for households, especially if current trends toward greater ownership of EVs and hybrids continue. High-income households also spend relatively more on tradeable goods, the prices of which are more sensitive to transport costs that would increase in response to a commercial VMT. Adopting either type of VMT would therefore likely be less regressive than the current gasoline tax.

As various policies encourage alternatives to driving, such as public transit, the role of user fees and other means of financing this infrastructure will attract greater attention. We also find that user charges for various forms of public transportation vary in their distributional burdens. Many public transit authorities already offer discounts based on life stage, such as student or senior discounts, in line with reduced fare requirements for authorities that receive federal funding (CFR Title 49, Section 609). Some also offer low-income fare adjustments. These provisions have important effects in improving the progressivity of user fees for financing these transportation modes. The IIJA includes more than $100 billion for public transportation, with equity and modernization highlighted as key policy goals. User fees financing could provide a way of expanding the revenue base for new public transit projects. We hope to consider in future work how various public transportation policies that create differentials in user fees across households with different average incomes affect the progressivity or regressivity of these fees.

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Appendix

A Predicting Expenditures in the NHTS

In order categorize households in the NHTS data by expenditure bin, we must impute household expenditures. To do this, we estimate an income-expenditure profile, taking into consideration household characteristics. We first regress expenditure in the CEX data for the 2000-2019 sample using a suite of socioeconomic and demographic characteristics, state and year fixed effects. These include a fourth order polynomial in a household's real income (2017 $s), indicators for household head's race, Hispanic status, whether they are employed, retired, a student, a homeowner, or male. We include the age-education profile by adding age in 5 year bins, education level, and the full set of age bin and education interactions. For household size, we include bins for family size, indicators for number of children, the head of household's marital status, and the interactions between marital status and number of children. Finally, we include year and state dummies. All of these explanatory variables for expenditure can be found in both the CEX and NHTS datasets. We weight the regression by the population weights in the CEX.

Results from predicting expenditure on the suite of socioeconomic and demographic characteristics, as well as year and time dummies, are presented in Appendix Table 6, column (1). We see that each additional dollar of income is estimated to lead to $0.31 in additional expenditure. The R^2 is 0.36, suggesting there is a lot of variation in expenditure not captured by demographics, socioeconomic characteristics, location, or time.

[Appendix Table 6 here]

We store all of the coefficients on our explanatory variables for expenditure and use them to construct a predicted expenditure in the NHTS data for the 2001, 2009 and 2017 surveys. Before doing so, we harmonize variable definitions where required. For example the NHTS classifies education bins differently in 2001 vs. 2009/2017, and differently from the CEX. We also impute income in the NHTS, as income is only provided in binned ranges. We set household income to the median of a bin's income range, and put all income in 2017 $'s to be consistent with CEX values. Expenditure is then constructed at the linear sum of the predictive variables multiplied by their respective coefficients stored from the CEX regression.

To compare the model fit, we regress predicted expenditure on income in the CEX data, and predicted expenditure on imputed income in the NHTS and compare profiles. Utilizing the predicted expenditure on the right hand side for the CEX data has the benefit of including information from the socioeconomic and demographic characteristics, state and year dummies, without directly including them in the regression. This allows us a more consistent comparison to the NHTS predicted expenditure, which is mechanically constructed from those right hand side variables.

Column (2) shows the expenditure-income profile regressing predicted expenditures on true incomes in the CEX, while column (3) shows the expenditure-income profile regressing predicted expenditures on imputed incomes in the NHTS. Both point estimates show that an increase in income of around $1 yields an additional predicted expenditure of around $0.40, showing similar profiles across the two datasets. Our estimates of average expenditure for those without incomes are higher in the NHTS than the CEX data, suggesting NHTS survey respondents are on average, higher income.

B Technological Adoption and the Progressivity of the Gas Tax

This appendix presents a model that highlights the interplay between household income and the adoption of a energy-saving technologies. We assume that individuals choose one of two technologies, and their level of driving. The choice of technology determines the energy use per mile (denoted g_i), the fixed cost of purchase (denoted k_i) and the enjoyableness of driving (denoted α_i). All together. welfare from using technology "i" is defined as

(1) $Welfare = \left(Y - p_g g_i d - k_i\right)^{1-\rho} + \alpha_i d^{1-\rho},$

where Y is income, p_g represents the price of gas, d is the endogenous distance travelled and $\rho > 0$. We assume a benchmark technology "0" and an energy-saving technology 1, where $g_0 > g_1$. Condition upon the choice of technology i, the total spending of energy equals $\frac{(Y-k_i)}{1+\left(p_g^{\rho-1} g_i^{\rho-1} \alpha_i\right)^{\frac{-1}{\rho}}}$ and so this always increases with income. This is also increasing with the composite term $\alpha_i g_i^{\rho-1}$, which captures the the combined impact on the technology's marginal parameter on driving. The relationship between energy use and income can only be reversed because of the relationship between the technology adoption and income levels. The following proposition describes the link between green technology adoption and income, and it is proved in the appendix:

Proposition: (a) If $k_0 > k_1$ and $\frac{\alpha_1}{\alpha_0} > \left(\frac{g_1}{g_0}\right)^{1-\rho}$, then all individuals adopt the energy saving technology and gas consumption is always rising with income. If $k_0 < k_1$ and $\frac{\alpha_1}{\alpha_0} < \left(\frac{g_1}{g_0}\right)^{1-\rho}$, then no one adopts the energy saving technology and gas consumption is always rising with income.

(b) If $k_0 > k_1$ and$\left(\frac{g_1}{g_0}\right)^{1-\rho} > \frac{\alpha_1}{\alpha_0}$, then individuals adopt the clean technology if and only if Y>Y*, where Y* is a finite value of $Y > k_0$. Energy consumption rises continuously everywhere with Y, except at the point Y*. At Y=Y*, energy consumption increases discontinuously with Y if and only if $1 > \frac{Y*-k_0}{Y*-k_1} > \frac{\alpha_1 g_1^{\rho-1}}{\alpha_0 g_0^{\rho-1}}$.

(c) If $k_0 < k_1$ and$\left(\frac{g_1}{g_0}\right)^{1-\rho} < \frac{\alpha_1}{\alpha_0}$, then individuals adopt the clean technology if and only if Y>Y*, where Y** is a finite value of $Y > k_1$. Energy consumption rises continuously everywhere with Y, except at the point Y**. At Y=Y**, energy consumption decreases discontinuously with Y if and only if $\frac{Y{*}{*}-k_0}{Y{*}{*}-k_1} > \frac{\alpha_1 g_1^{\rho-1}}{\alpha_0 g_0^{\rho-1}} > 1$.

The conditions $\frac{Y{*}{*}-k_0}{Y{*}{*}-k_1} > \frac{\alpha_1 g_1^{\rho-1}}{\alpha_0 g_0^{\rho-1}}$ and $\frac{Y{*}-k_0}{Y{*}-k_1} > \frac{\alpha_1 g_1^{\rho-1}}{\alpha_0 g_0^{\rho-1}}$ are equivalent to the condition

$\frac{1+(p_g g_1)^{\frac{\rho-1}{\rho}} \alpha_1^{\frac{1}{\rho}}}{1+(p_g g_0)^{\frac{\rho-1}{\rho}} \alpha_0^{\frac{1}{\rho}}} > \left(\frac{(p_g g_1)^{\frac{\rho-1}{\rho}} \alpha_1^{\frac{1}{\rho}}}{(p_g g_0)^{\frac{\rho-1}{\rho}} \alpha_0^{\frac{1}{\rho}}}\right)^{1-\rho}$, which is written only in terms of exogenous variables.

This proposition details three possible scenarios for green technologies and the relationship between income and energy use. In the parameter ranges covered in Part (a) of the Proposition, the green technology is either adopted for all values of Y or not adopted for all values of Y. As all individuals use the same technology, and hence richer people use more energy.
The parameters discussed in Part (b) seem relevant for the 1970s and 1980s. Energy-saving cars, such as the Honda Civic, were typically much smaller and less expensive, than gas-intensive cars, like Cadillacs. The energy saving was created primarily by having less weight and less power. Consequently, the green technology is adopted by the poor rather than the rich. Energy use rises with income almost everywhere, and it may jump up with income at the point of technology adoption, as long as the price gap between the two cars isn't too large. If the up-front cost of two technologies is similar, which is guaranteed by $\frac{Y{*}-k_0}{Y{*}-k_1} > \frac{\alpha_1 g_1^{\rho-1}}{\alpha_0 g_0^{\rho-1}}$, then the post-purchase parameter aggregate $(\alpha_i g_i^{\rho-1})$ determine the change in energy use, and we have assumed $\alpha_0 g_0^{\rho-1} > \alpha_1 g_1^{\rho-1}$ in part (b).

If the up-front cost difference is larger, then this cost will have effectively an "income effect," which means that the Cadillac buyer is pushed to drive less. The condition that $\frac{Y{*}-k_0}{Y{*}-k_1} > \frac{\alpha_1 g_1^{\rho-1}}{\alpha_0 g_0^{\rho-1}}$ ensures that the "substitution effects" associated with the Cadillac (more fun to drive and more gas per mile) overwhelm that income effect

The parameters discussed in Part (c) are oriented towards new expensive technologies that reduce energy use, but cost more. Tesla reduce energy use, but they are also typically more powerful and quieter. The proposition predicts that if $k_0 < k_1$ and $\left(\frac{g_1}{g_0}\right)^{1-\rho} < \frac{\alpha_1}{\alpha_0}$, then the green technology is adopted by the rich. Again, energy use is rising almost everywhere with income, but in this case, energy use jumps downward with income at the point of adoption if k_0 low relative to k_1, that $\frac{Y{*}{*}-k_0}{Y{*}{*}-k_1} > \frac{\alpha_1 g_1^{\rho-1}}{\alpha_0 g_0^{\rho-1}} > 1$ holds. In this case, price inequality is needed to generate the added income effect that pushes driving down for the Tesla driver. It is not enough for the Tesla just to be gas efficient to satisfy this condition, given our functional form, because improvements in gas mileage are offset by extra driving.

Proof of Proposition: (a) Conditional upon adopting technology "i", the optimal level of driving satisfies $d_i^* = \frac{\alpha_i^{\frac{1}{\rho}}(Y-k_i)}{(p_g g_i)^{\frac{1}{\rho}}+p_g g_i \alpha_i^{\frac{1}{\rho}}}$, which implies that welfare is $\left(1+\left(p_g g_i\right)^{\frac{\rho-1}{\rho}}\alpha_i^{\frac{1}{\rho}}\right)^{\rho}(Y-k_i)^{1-\rho}$.

Consequently the net benefit of adoption technology 1 can be written as:

$$\text{(A1)}\ F(Y) = \left(1+\left(p_g g_1\right)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}\right)^{\rho}(Y-k_1)^{1-\rho} - \left(1+\left(p_g g_0\right)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}\right)^{\rho}(Y-k_0)^{1-\rho},$$

which is positive if and only if $\frac{1+\left(p_g g_1\right)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}}{1+\left(p_g g_0\right)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}} > \left(\frac{Y-k_0}{Y-k_1}\right)^{\frac{1-\rho}{\rho}}$.

If $k_0 > k_1$ and $\frac{\alpha_1}{\alpha_0} > \left(\frac{g_1}{g_0}\right)^{1-\rho}$, then $1+\left(p_g g_1\right)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}} > 1+\left(p_g g_0\right)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}$ and $(Y-k_1)^{1-\rho} > (Y-k_0)^{1-\rho}$ for all values of Y and consequently all income groups adopt.

If $k_0 < k_1$ and $\frac{\alpha_1}{\alpha_0} < \left(\frac{g_1}{g_0}\right)^{1-\rho}$, then $1+\left(p_g g_1\right)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}} < 1+\left(p_g g_0\right)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}$ and $(Y-k_1)^{1-\rho} < (Y-k_0)^{1-\rho}$ for all values of Y and consequently no income groups adopt.

(b) If $k_0 > k_1$ and $\frac{\alpha_1}{\alpha_0} < \left(\frac{g_1}{g_0}\right)^{1-\rho}$, then $0 < \frac{1+\left(p_g g_1\right)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}}{1+\left(p_g g_0\right)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}} < 1$, and the inequality can be written as or $Y < \frac{\left(1+(p_g g_0)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}\right)^{\frac{\rho}{1-\rho}} k_0 - \left(1+(p_g g_1)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}\right)^{\frac{\rho}{1-\rho}} k_1}{\left(1+(p_g g_0)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}\right)^{\frac{\rho}{1-\rho}} - \left(1+(p_g g_1)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}\right)^{\frac{\rho}{1-\rho}}} = Y*$.

Hence there is a value of Y, denoted Y*, at which $\frac{1+(p_g g_1)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}}{1+(p_g g_0)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}} = \left(\frac{Y-k_0}{Y-k_1}\right)^{\frac{1-\rho}{\rho}}$. For all values of Y>Y*, welfare is higher with technology 0. For all values of Y<Y*, welfare is higher with technology 1. Miles travelled and hence gas consumption is increasing continuously at all levels of Y other than Y* (because within a technology $d = \frac{\alpha_i^{\frac{1}{\rho}}(Y-k_i)}{(p_g g_i)^{\frac{1}{\rho}} + p_g g_i \alpha_i^{\frac{1}{\rho}}}$) but at Y*, gas consumption jumps from from $g_1 d_1^*$ to $g_0 d_0^*$,, where $g_i d_i^* = \frac{\left(\alpha_i g_i^{\rho-1}\right)^{\frac{1}{\rho}}(Y-k_i)}{(p_g)^{\frac{1}{\rho}} + p_g\left(\alpha_i g_i^{\rho-1}\right)^{\frac{1}{\rho}}}$. Using the fact that $\frac{1+(p_g g_1)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}}{1+(p_g g_0)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}} = \left(\frac{Y*-k_0}{Y*-k_1}\right)^{\frac{1-\rho}{\rho}}$, then inequality simplifies to $\frac{Y*-k_0}{Y*-k_1} > \frac{\alpha_1 g_1^{\rho-1}}{\alpha_0 g_0^{\rho-1}}$, or $\frac{1+(p_g g_1)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}}{1+(p_g g_0)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}} > \left(\frac{(p_g g_1)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}}{(p_g g_0)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}}\right)^{1-\rho}$

(c) If $k_0 < k_1$ and $\frac{\alpha_1}{\alpha_0} > \left(\frac{g_1}{g_0}\right)^{1-\rho}$, then $\frac{1+(p_g g_1)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}}{1+(p_g g_0)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}} > 1$, and the inequality can be written

$$Y > \frac{\left(1+(p_g g_1)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}\right)^{\frac{\rho}{1-\rho}} k_1 - \left(1+(p_g g_0)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}\right)^{\frac{\rho}{1-\rho}} k_0}{\left(1+(p_g g_1)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}\right)^{\frac{\rho}{1-\rho}} - \left(1+(p_g g_0)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}\right)^{\frac{\rho}{1-\rho}}} = Y**.$$

Hence there exists a value of Y, denoted Y** at which $\frac{1+(p_g g_1)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}}{1+(p_g g_0)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}} = \left(\frac{Y-k_0}{Y-k_1}\right)^{\frac{1-\rho}{\rho}}$ and for all values of Y below Y**, individuals choose technology 0 and for all values of Y above Y**, individuals choose technology 1. Gas consumption will drop discontinuously down as income rises at the point if and only if $\frac{Y{**}-k_0}{Y{**}-k_1} > \frac{\alpha_1 g_1^{\rho-1}}{\alpha_0 g_0^{\rho-1}} > 1$ or $\frac{1+(p_g g_1)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}}{1+(p_g g_0)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}} > \left(\frac{(p_g g_1)^{\frac{\rho-1}{\rho}}\alpha_1^{\frac{1}{\rho}}}{(p_g g_0)^{\frac{\rho-1}{\rho}}\alpha_0^{\frac{1}{\rho}}}\right)^{1-\rho}$.

C Forecasting the Vehicle Fleet in the NHTS

C.1 Constructing the Annual Vehicle Fleet

In order to examine how the distribution of user fees paid on personal vehicles will change over time, we need to have an idea of how the personal vehicle fleet will evolve. In this section, we walk through the steps to predict the composition of the vehicle fleet, by year, through 2042. First, we collect data on light vehicle sales from the *Transportation Energy Data Book, Edition 39*, produced by Oak Ridge National Laboratory for the Department of Energy. We have data on all sales between 2000 and 2020; for post-2020, we regress total light vehicle sales on a time trend, and predict out to 2042.

To understand the change in the light vehicle stock over time, we collect data on annual vehicle registrations, again from the *Transportation Energy Data Book, Edition 39.* We allow registrations to grow by 0.7% per year post-2020, the average growth rate between 2000 and 2020. Annual registrations then give us the net change in the vehicle fleet, after accounting for sales and retirement.

In order to change the composition of HEV and gasoline powered vehicles over time, we need a forecast of how many HEV vehicles we expect on the road each year, as well as gasoline vehicles, and retired vehicles. Unfortunately, we do not have predictions for stocks, but a variety of consulting firms have made their own predictions for sales shares. Among the many predictions, Deloitte predicts 27% of sales will be HEV by 2030, Ford predicts 40% will be EV by 2030, KPMG predicts 52% EV by 2030.. We fit a logistic function to proxy for an adoption curve, target the two parameters to fit real adoption between 2000 and 2020, and set the mid-point for full HEV sales at 2032, in line with the predictions listed above:

$$SalesShare_t^{HEV} = \frac{1}{1 + e^{-0.25(t-2032)}}$$

Appendix Figure 14 plots out our sales adoption curve in panel (a). We see that HEV sales outstrip gas vehicle sales after 2032, as calibrated, and gasoline sales drop to nearly 0 by the mid 2040’s. Panel (b) highlights that changes in stock are much slower to respond to even highly dominated HEV sales. While sales of HEV pass 50% in 2032, the stock of vehicles is less than 20% HEV. It takes another 5 years for the vehicle stock to reach 1/3rd HEV, at which point HEV sales comprise 80% of all sales.

With predicted HEV sales shares, predicted sales, and annual registrations, we can back out how many vehicles are retired from the fleet each year:

$$\Delta registrations_{t+1,t} = Sales_t^{HEV} + Sales_t^{gas} - Retire_t$$

Appendix Table 7 shows the evolution of the vehicle fleet from 2000 to 2037. Over that time, we can expect to add 92,407,000 HEV vehicles and 205,730,000 gasoline vehicles to the fleet, while we remove 260,748,000 vehicles.

[Insert Appendix Table 7]

But this still does not yield the share of stock over time. For that, we need to know initial conditions for HEVs, *X*, and gasoline vehicles, *Y*.

Year	Registered Vehicles	Hybrid/Electric Vehicles	Gas Vehicles
2017	248,926	*X*	*Y*
2037	286,314	*X*+92,407	*Y*+205,730-260,748

Note: All vehicle counts in millions.

Let $X = \sum_{1999}^{2017} Sales_t^{HEV}$, since we know there were 0 sales and 0 stock in 1999 for HEVs. Then take $Y = Registrations_{2017} - X$. We assume all retired vehicles are gasoline vehicles.

Year	Registered Vehicles	Hybrid/Electric Vehicles	Gas Vehicles
2017	248,926	5,387	243,539
2037	286,314	97,794	188,521

Note: All vehicle counts in millions.

We see that the total vehicle fleet grows by 15%, but HEVs grow from approximately 2% of the vehicle fleet in 2017 to just over 34% in 2037. We stop our forecast in 2037, as this is the first year in which HEVs comprise 1/3rd of the vehicle stock.

C.2 Creating a Forecast for the 2037 NHTS

We observe 229,324 surveyed vehicles in the NHTS (with positive expenditure and miles driven). To create a 2037 NHTS forecast, we first expand the vehicle stock to 263,723 vehicles, by increasing the number of vehicles in each expenditure decile by 15%. Crucially, we do not do this equally by vehicle type.

$$Stock_{2037}^{HEV} = 0.34 \times 1.15 \times 229{,}324 = 89{,}666$$

and

$$Stock_{2037}^{gas} = 0.66 \times 1.15 \times 229{,}324 = 174{,}056$$

We also need to determine how to distribute the total stock of HEVs and gasoline vehicles across expenditure deciles. We assume that the distribution we observe in 2017 will remain constant over time, with the highest spending groups also being the first to adopt HEVs.

[Insert Appendix Table 8]

Appendix Table 8 outlines the 2017 NHTS vehicle composition, by expenditure decile. The 2017 data have 223,639 gasoline and 5,685 hybrid/electric vehicles surveyed. The lowest expenditure decile only has 41 HEVs observed in the data, and this monotonically increases until we arrive at the highest expenditure decile, with 1,526 observed HEVs. This means that about 27% of all HEVs observed in the data belong to the highest expenditure decile households, will less than 1% of HEVs belong to the lowest decile households. Fixing these shares from column 5 in Appendix Table 8, and applying them to the $Vehicles^{2037}$yields HEV^{2037}, by decile. Gas^{2037} is then ($Vehicles^{2037} - HEV^{2037}$).

Finally, we calculate the change in the number of vehicles, the change in HEV stock, and change in gasoline stock, for each expenditure decile. This guides us in how we add observations to the baseline 2017 dataset to arrive at a 2037 dataset we can use for analysis and policy proposals.

To expand our 2017 NHTS sample, we proceed in three steps. First, we duplicate a random sample of observations in each expenditure decile. Second, we allocate the duplicated observations to either being a gasoline vehicle or HEV. In deciles with new gasoline vehicles, $\Delta Gas > 0$, all HEV vehicles that were randomly duplicated remain HEV, we randomly allocate the remaining $\Delta Vehicles$ between gasoline and HEV, according to their 2037 targets. For deciles that lose gasoline vehicles, we recode all randomly duplicated vehicles at HEV, then randomly reassign original gasoline vehicle observations as HEV until we hit the 2037 HEV and gasoline targets. Finally, we randomly allocate new HEVs as either electric or hybrid, with 60% and 40% shares, respectively. New electric vehicles have a gas/mile of 0, and new hybrid vehicles are assigned gas/mile of 0.025, or the mean 1/MPG for the 2017 hybrid sample.

The final 2037 forecasted dataset has a vehicle stock that is 66% gasoline, 15% hybrid, and 19% electric, compared to the 2017 observed dataset that is 97.5% gasoline, 2.3% hybrid, and 0.1% electric.

Tables

Table 1: Tax per Mile ($'s), by Proposal

Proposal	τ/gallon (cents)	τ/mile (cents)
Baseline Federal Gas Tax	18.4	μ=0.89*
Match Current Effective Tax/Mile (τ_1)		0.89
Fully Fund the HTF: Gasoline Tax (τ_2), 60/40 EV/HV	72.7	μ=3.23*
Fully Fund the HTF: VMT (τ_3), 60/40 EV/HV		2.6

Notes: Top two rows use data from the National Household Travel Survey, 2017, vehicle level dataset. All taxes funding the 2021-2025 mean outlays for the HTF use 2037 forecasted NHTS panel. This table summarizes the taxes used in the proposals outlined in section 5. *mean τ/mile only calculated for hybrid and gasoline vehicles as electric do not pay the tax.

Table 2: Mean Taxes Paid by Expenditure Decile: Fully Funding HTF with VMT

	Baseline ($'s)	Paid (no ΔMiles) ($'s)	Paid (ΔMiles) ($'s)
	Gasoline Vehicles		
1	91	291	276
2	121	367	348
3	151	449	426
4	177	514	488
5	192	539	511
6	207	552	524
7	231	571	542
8	235	540	513
9	255	516	490
10	256	450	427
	Hybrid Vehicles		
	Baseline ($'s)	Paid (no ΔMiles) ($'s)	Paid (ΔMiles) ($'s)
1	29	221	176
2	67	254	202
3	57	305	243
4	71	369	293
5	54	439	349
6	59	429	342
7	59	428	341
8	58	475	378
9	66	488	388
10	70	529	421
	Electric Vehicles		
	Baseline ($'s)	Paid (no ΔMiles) ($'s)	Paid (ΔMiles) ($'s)
1	0	244	214
2	0	262	230
3	0	257	225
4	0	334	293
5	0	355	311
6	0	363	318
7	0	405	355
8	0	420	369
9	0	457	401
10	0	452	397

Notes: This table shows the mean amount of federal taxes paid per household, by vehicle type and expenditure decile, for three scenarios. In the first column, we present annual federal fuel taxes paid by vehicle type under the current federal gasoline tax. In the second column, we present annual user fees paid under our VMT proposal, assuming no change in driving behavior induced by the change in tax scheme. In the final column, we present annual user fees paid under our VMT proposal, allowing for driving behavior to respond to changes in per mile driving costs induced by switching from a gasoline tax to a VMT. We calibrate the VMT to fully fund the HTF, use the 2037 forecasted vehicle fleet, with a 60/40 electric-hybrid breakdown of new vehicles. For households with multiple types of vehicles (i.e. a gasoline vehicle and a hybrid vehicle), total payment is split across the categories.

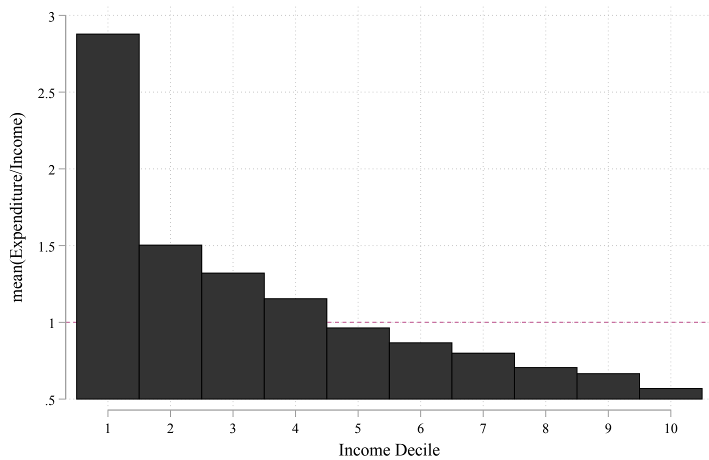
Table 3: Comparing Out-of-Pocket Costs for Households (annual $'s)

Expenditure Decile	1	2	3	4	5	6	7	8	9	10
Gasoline Tax (Fully Funding HTF)	364	467	574	666	675	700	713	684	646	504
VMT (Fully Funding HTF)	283	378	473	545	600	642	712	734	790	777
Diesel Taxes	4	6	8	10	12	13	15	18	23	36

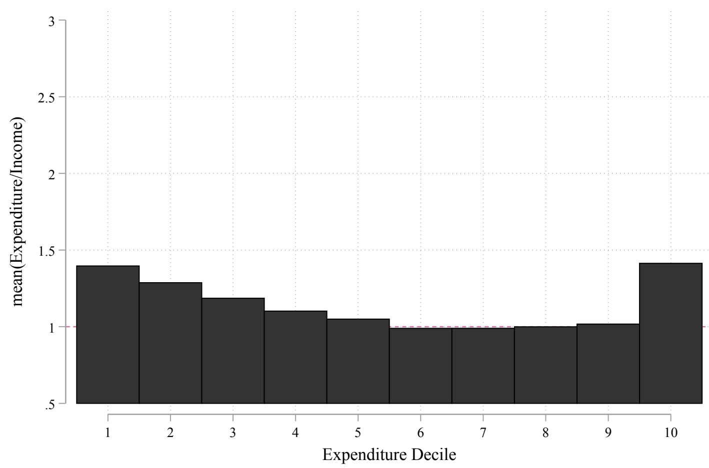
Notes: This table shows annual out-of-pocket costs for households, in $'s, for the various fuel-related user fees considered. The top row shows the mean gasoline tax paid annually, using the 2037 forecast vehicle fleet in conjunction with a gasoline tax calibrated to fully fund the HTF. The second row show the mean VMT paid annual, using the 2037 forecast vehicle fleet with a VMT calibrated to fully fund the HTF. The bottom row shows the mean user fees paid by consumers of final goods that use truck transportation, assuming an additional $0.03 VMT added to commercial trucking, on top of the existing diesel tax.

Figures

Figure 1: *Expenditure/Income* by Income and Expenditure Decile, 2017 CEX



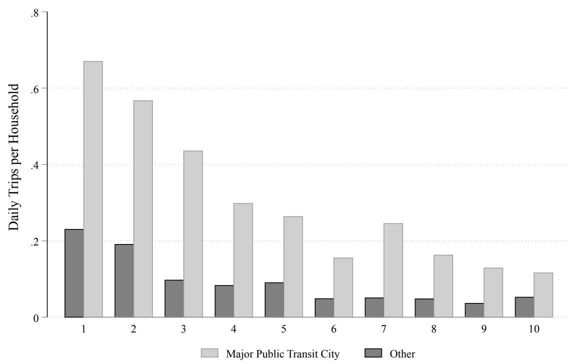
(a) Income Deciles



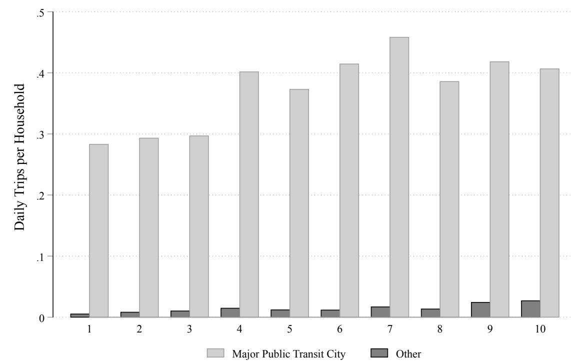
(b) Expenditure Deciles

Notes: Data from the Survey of Consumer Expenditures, 2017. Panel (a) shows the average *Expenditure/Income* ratio within income deciles. Panel (b) shows the same ratio, averaged within expenditure deciles. All ratios winsorized at the 5^{th} and 95^{th} percentiles, for ease of inspection.

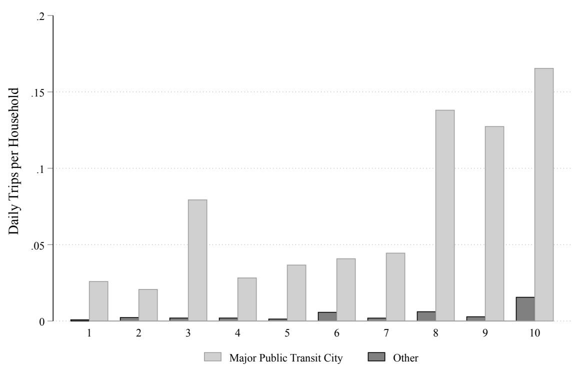
Figure 2: Public Transit Utilization in the NHTS, by Expenditure Decile



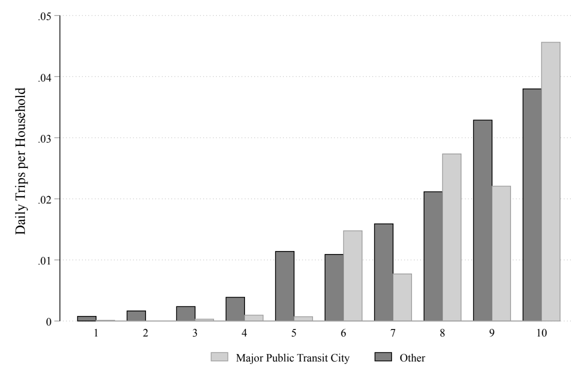
(a) Bus



(b) Subway



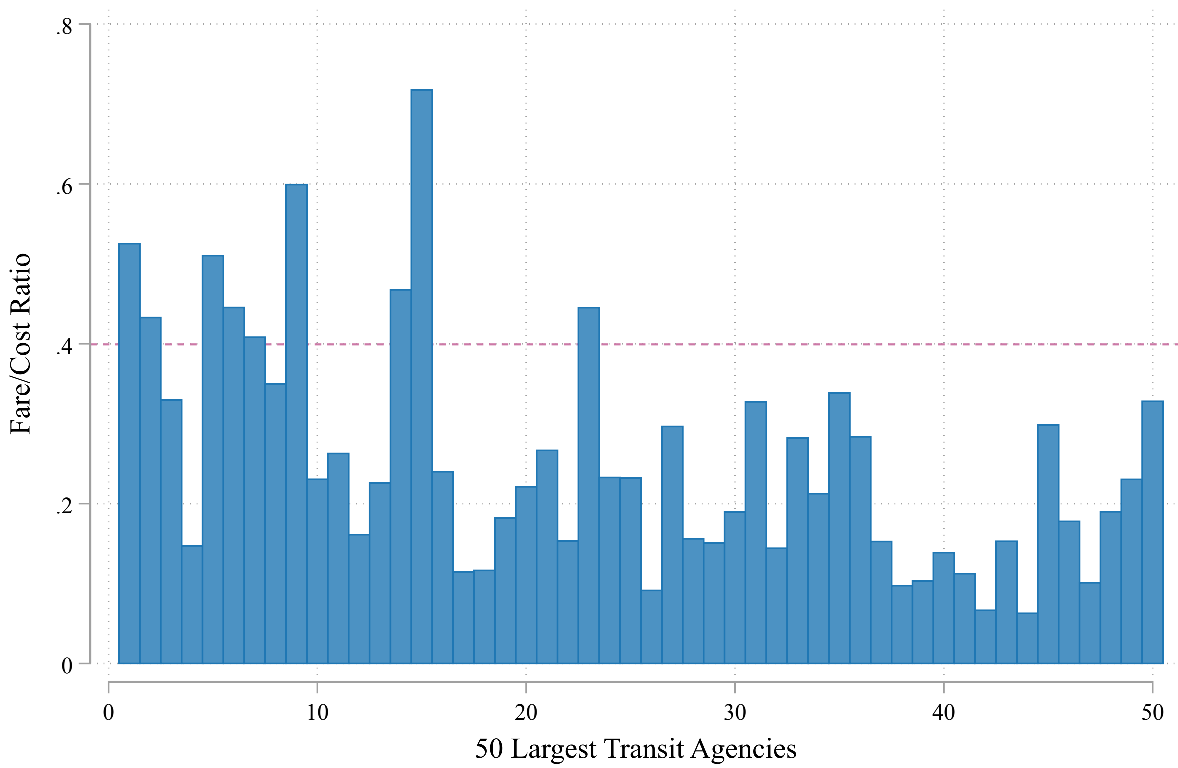
(c) Commuter Rail



(d) Air Travel

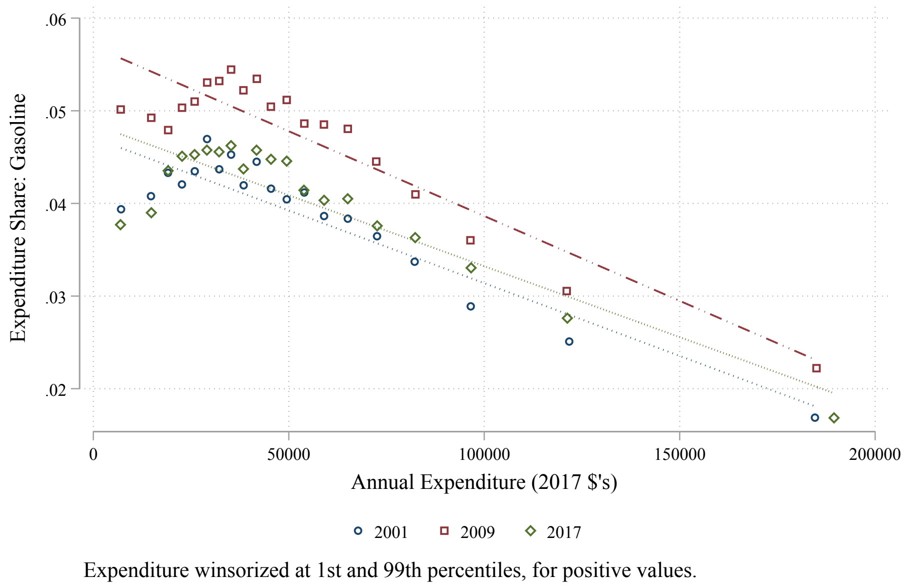
Notes: Data from the National Household Travel Survey, 2017, trip level dataset aggregated to households. Panel (a) shows the distribution of daily household trips by bus, panel (b) by subway, panel (c) by commuter rail, and panel (d) trips that paid tolls. Figures do not include households with negative expenditure. All figures split by a city's status as a major public transit city: New York City, Chicago, Boston, Washington, DC, Philadelphia and San Francisco.

Figure 3: Public Transit Fares as Share of Operating Costs

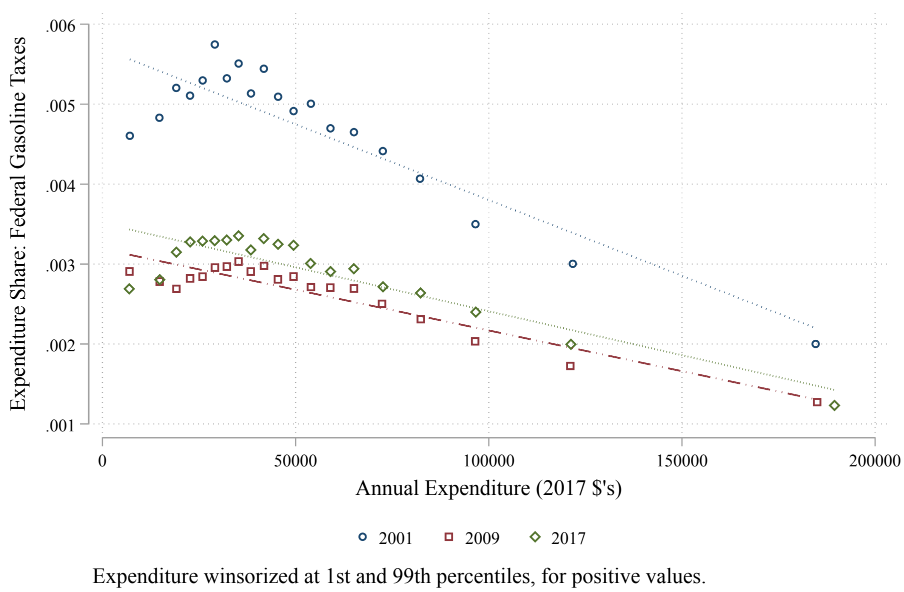


Notes: Data from the National Transit Database, 2019. The figure shows the ratio of average passenger fare to average operating costs, exclusive of capital costs, for the 50 largest transit authorities, as measured by their operating expenses. Transit authorities may offer multiple travel modes; we average over modes within authority, weighted by ridership. The dashed line calculates the unlinked passenger trips weighted average fare/cost ratio across the top 50 largest authorities.

Figure 4: Gasoline and Fuel Tax Expenditures in the CEX, by Expenditure Level



(a) Gasoline

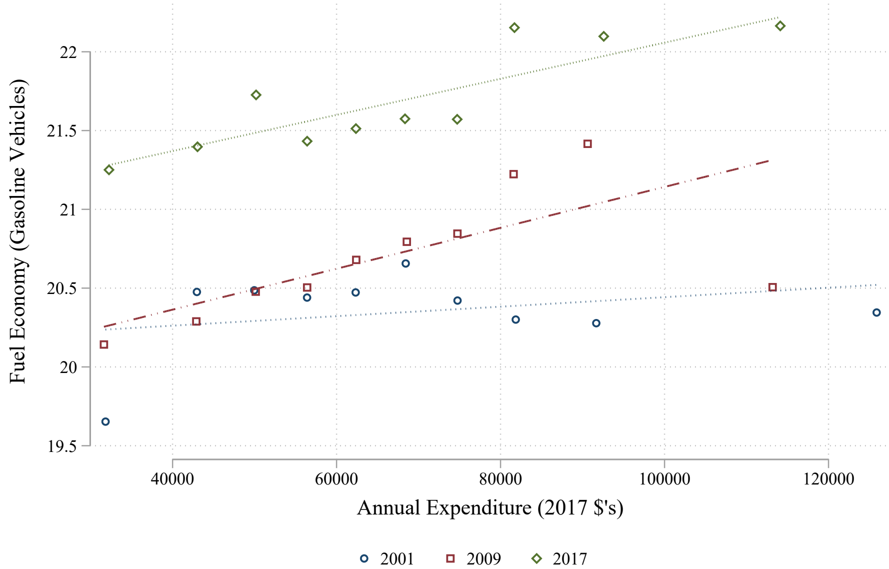


(b) Federal Taxes

Notes: Data from the CEX waves from 2001, 2009 and 2017. All panels plot binned scatters and their associated linear fits. Panel (a) shows the average expenditure share devoted to gasoline by expenditure ventile. Panel (b) plots the expenditure share devoted to federal fuel taxes by expenditure ventile. Expenditure is winsorized at the 1^{st} and 99^{th} percentiles prior to binning, for positive values of expenditure. Data on annual fuel prices by state or region from the Energy Information Administration's "all grades all formulations" retail price average.

Figure 5: Vehicle Characteristics in the NHTS, by Expenditure Level

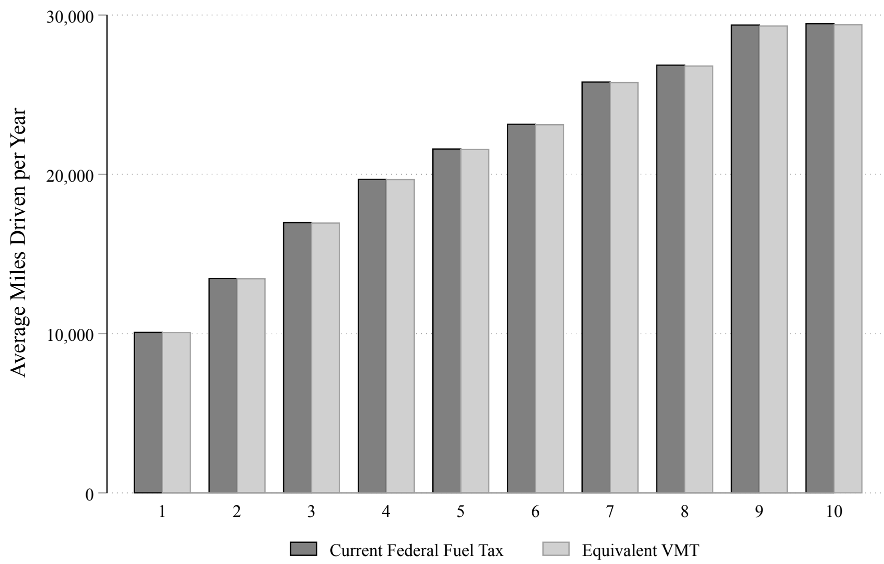
(a) Share Hybrid/Electric



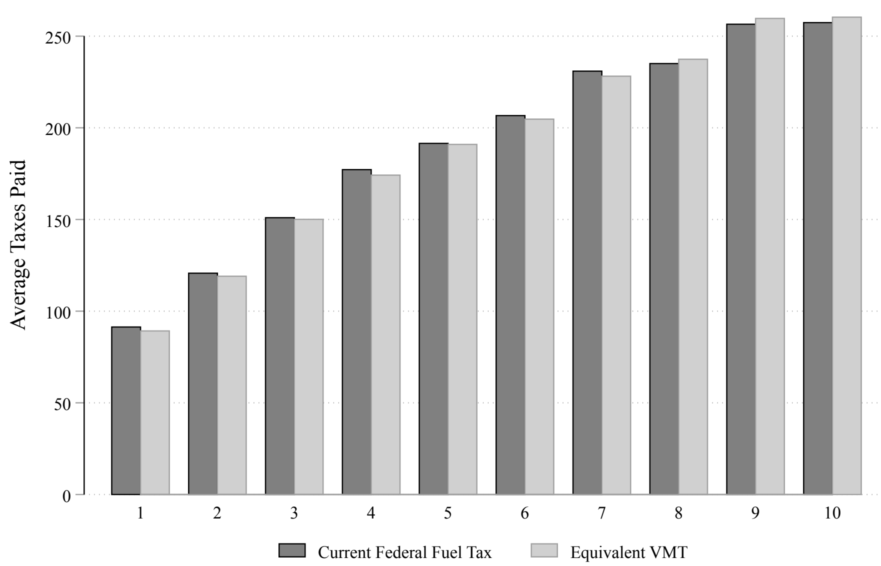
(b) Fuel Economy

Notes: Data from the NHTS waves from 2001, 2009 and 2017. All panels plot binned scatters and their associated linear fits. Panel (a) shows the share of vehicle identified as hybrid or electric, by expenditure ventile; note that there was no indication available in 2001. Panel (b) shows mean fuel economy, by expenditure ventile. Expenditure is winsorized at the 1^{st} and 99^{th} percentiles prior to binning, for positive values of expenditure.

Figure 6: Baseline (2017) vs. Revenue Neutral VMT (2017)



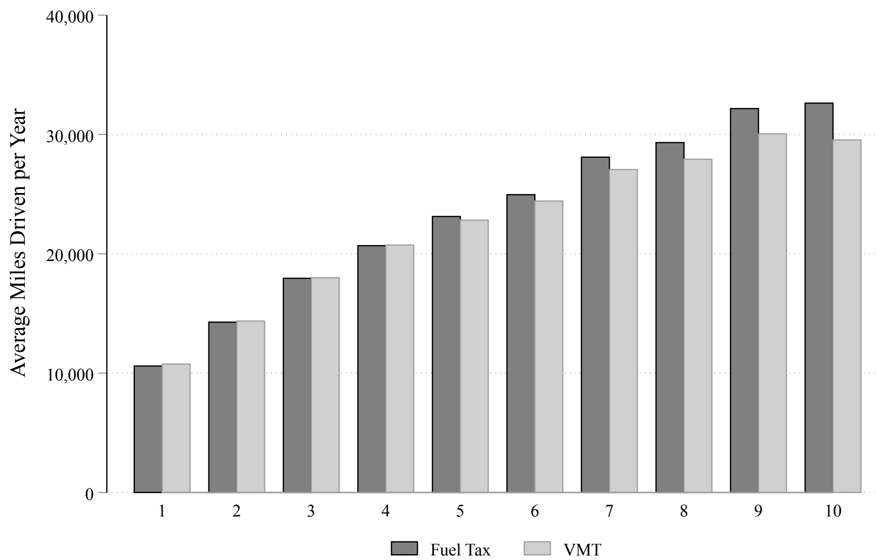
(a) Mean Miles



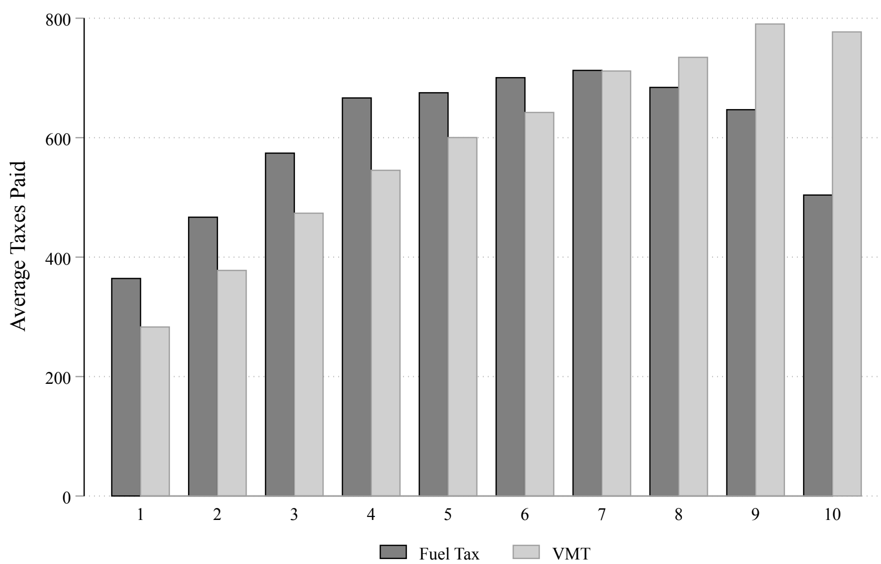
(b) Mean Federal Taxes Paid

Notes: Data from the 2017 NHTS. Panels show the mean miles traveled and mean federal taxes paid, comparing the current gasoline tax and proposed revenue-neutral vehicle miles tax (VMT). All results conditional on having positive predicted expenditures.

Figure 7: Fully Fund HTF with Gas Tax vs. Fully Fund HTF with VMT (2037)



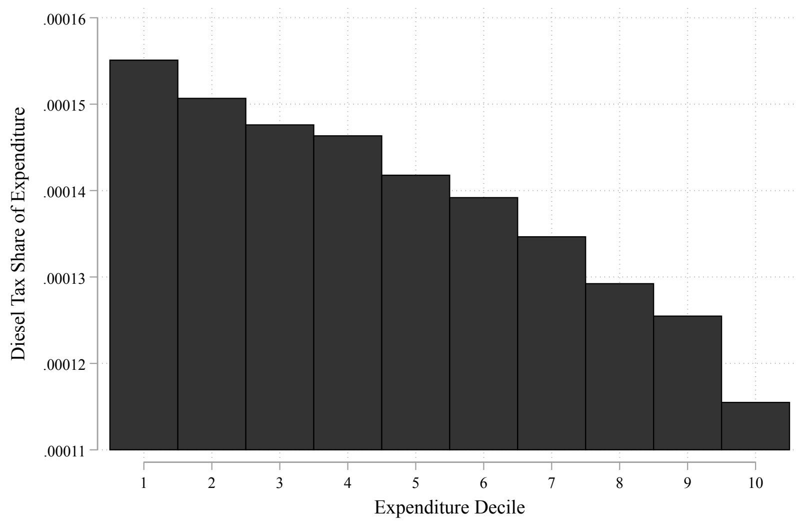
(a) Mean Miles



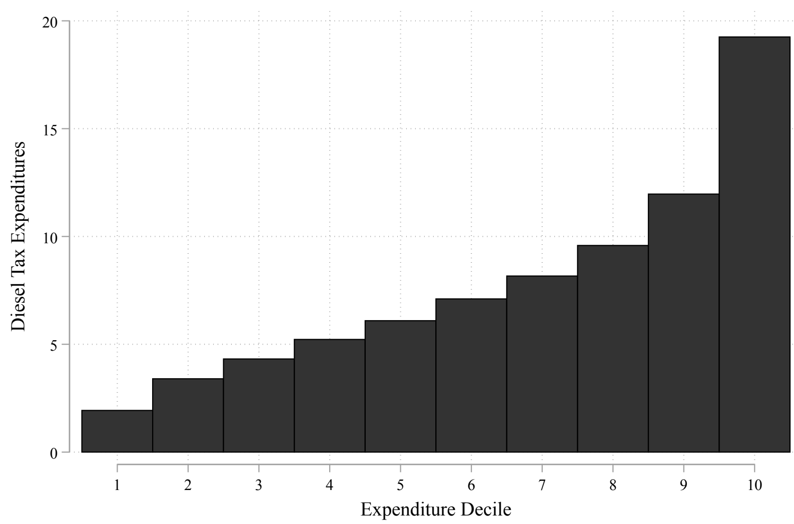
(b) Mean Federal Taxes Paid

Notes: Data from the 2017 NHTS. Panels show the mean miles traveled and mean federal taxes paid, comparing a gasoline tax and a vehicle miles tax calibrated to fully fund the 2021-2025 HTF. The figures use the 2037 forecasted vehicle fleet, assuming a 60/40 split of new non-gasoline vehicles by electric and hybrid. All results conditional on having positive predicted expenditures.

Figure 8: Diesel Tax Shares and Amount Paid Annually, by Expenditure Decile



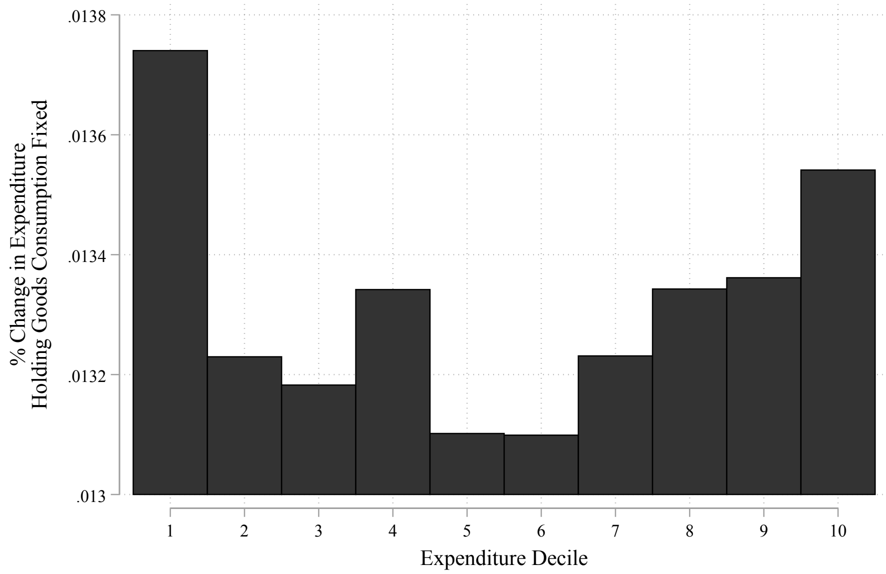
(a) Diesel Tax Share of Total Expenditures



(b) Diesel Tax Expenditures ($'s)

Notes: BEA IO tables, CEX 2019.

Figure 9: Change in Expenditure Needed to Maintain Original Consumption Basket, by Expenditure Decile



Notes: BEA IO tables, CEX 2019. The figure presents the amounts of additional expenditure needed to purchase the original consumption bundle observed in the CEX, under the adoption of a new federal VMT of $0.03/mile.

A Appendix Tables

Table 4: Replication of 2019 Consumer Expenditure Survey, Table 1203

Item	All	< $15,000	$15,000-$29,999	$30,000-$39,999	$40.000-$49,999	$50,000-$69,000	$70,000-$99,999	$100,000-$149,000	$150,000-$199,999	$200,000+
Table 1203										
Number of CU's	132,242	15,848	19,856	12,991	11,208	17,470	19,119	18,225	8,266	9,260
Pre-Tax Income	$82,852	$7,574	$22,189	$34,772	$44,831	$59,328	$83,558	$121,433	$171,061	$343,498
Annual Expenditure	$63,036	$26,194	$34,201	$40,942	$47,299	$54,212	$66,801	$84,994	$109,020	$160,318
Gas, other fuels, motor oil	$2,094	$970	$1,170	$1,699	$1,864	$2,153	$2,496	$2,927	$3,181	$3,283
Replication of Table 1203 using PUMD										
Number of CU's	132,242	15,742	19,720	12,910	11,145	17,432	19,044	17,885	7,477	10,815
Pre-tax Income	$82,451	$7,368	$22,048	$34,643	$44,679	$59,122	$83,592	$120,952	$170,183	$309,772
Annual Expenditure	$59,280	$24,716	$31,944	$39,308	$44,086	$50,980	$63,647	$79,859	$99,337	$142,784
Gas, other fuels, motor oil	$2,094	$961	$1,171	$1,701	$1,863	$2,142	$2,507	$2,911	$3,177	$3,223

Notes: This table replicates Table 1203 from the Survey of Consumer Expenditures annual release, for the year 2019. Replication errors occur due to sampling and adjustments made to the public use microdata in order to maintain consumer unit anonymity.

Table 5: Joint Distribution of Expenditure and Income Deciles

Income Decile	Expenditure Decile 1	2	3	4	5	6	7	8	9	10
1	49	18	11	7	5	3	3	2	1	2
2	32	28	15	9	5	4	3	2	1	1
3	12	25	20	15	11	6	4	3	2	3
4	4	14	22	18	15	9	6	4	3	3
5	2	8	16	20	18	15	9	5	4	3
6	1	4	10	15	18	18	14	9	6	5
7	0	1	4	9	15	20	20	15	8	7
8	0	1	2	5	8	15	22	23	17	8
9	0	0	1	2	4	9	16	23	29	18
10	0	0	0	0	1	2	5	11	28	51
Expenditure Decile	**Income Decile 1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	50	31	11	4	2	1	0	0	0	0
2	19	28	25	14	8	4	1	1	0	0
3	12	15	19	22	16	10	4	2	1	0
4	7	9	15	19	20	15	9	5	2	0
5	5	4	11	15	18	18	16	8	4	1
6	3	3	5	9	14	18	20	15	9	2
7	3	3	4	6	9	13	20	23	15	5
8	2	2	3	5	5	9	16	24	23	12
9	1	1	2	3	4	6	8	17	29	28
10	2	1	2	3	3	5	7	8	17	51

Notes: Entries in each panel denote the percentage of customer units in the income or expenditure decile listed in the row that are found in the income or expenditure decile in the column, as in Poterba (1990). Calculations based on the 2017 Consumer Expenditure Survey.

Table 6: Actual and Predicted Expenditure-Income Profiles

	CEX		NHTS
	(1)	(2)	(3)
	Exp_i	$\widehat{Exp}_i$	$\widehat{Exp}_i$
Inc_i	0.31	0.41	
	(0.003)	(0.000)	
$\widehat{Inc}_i$			0.40
			(0.001)
$Constant$	8,625	25,542	32,195
	(1879)	(17)	(74)
Covariates	yes	no	no
R^2	0.36	0.90	0.47
N	644,240	644,240	312,204

Notes: This table shows the output from regressing $Exp_i = \alpha + \beta Inc_i + Covariates_{it} + \varepsilon_i$ in column (1), $\widehat{Exp}_i = \alpha + \beta Inc_i + \varepsilon_i$ in column (2), and $\widehat{Exp}_i = \alpha + \beta \widehat{Inc}_i + \varepsilon_i$ in column (3). Columns (1) and (2) use data from the CEX, 2000-2019. Column (3) uses data from the 2001, 2009 and 2017 NHTS. $\widehat{Exp}_i$ in column (2) predicted as discussed in [[INSERT SECTION HERE]] using CEX data; $\widehat{Exp}_i$ in column (3) constructed using the parameters estimated in [[INSERT SECTION HERE]]and applying them to the NHTS data; $\widehat{Inc}_i$ set to the median income value for the income bins provided in NHTS as no continuous income is provided. Standard errors in parentheses.

Table 7: Forecasting Vehicle Registrations, Sales and Retirement

Year	$\Delta Registrations_{t,t-1}$	$\widehat{Sales}_t$	$\widehat{share^{HEV}}_t$	$Sales_t^{HEV}$	$Sales_t^{Gas}$	$Retire_t$
2017	3249	16827	3.3	555	16272	13578
2018	673	16919	3.9	660	16259	16246
2019	2931	16630	4.2	698	15932	13699
2020	1768	14114	5.4	762	13352	12346
2021	1781	15055	6.6	995	14060	13275
2022	1793	15015	8.1	1215	13800	13222
2023	1805	14975	9.9	1483	13492	13169
2024	1818	14934	12.2	1810	13124	13117
2025	1830	14894	14.8	2210	12685	13064
2026	1843	14854	18.2	2697	12157	13011
2027	1856	14814	22.2	3293	11521	12958
2028	1869	14774	27.2	4019	10755	12905
2029	1882	14734	33.3	4906	9828	12851
2033	1936	14573	56.2	8193	6380	12638
2034	1949	14533	62.2	9046	5487	12584
2035	1963	14493	67.9	9843	4650	12530
2036	1976	14453	73.1	10566	3887	12476
2037	1990	14413	77.7	11203	3210	12422
		Totals		92,407	205,730	260,748

Data on vehicle registrations and sales by fuel type from *Transportation Energy Data Book, Edition 39* produced by Oak Ridge National Laboratory for the Department of Energy. Sales and share hybrid/electric based on data up to 2020; registration data through 2019. Additional years authors' forecast. Registrations, sales, and retirement in 1000's.

Table 8: Creating a Forecast for 2037 NHTS Data

Decile	Vehicles^{2017}	HEV^{2017}	Gas^{2017}	P(Decile|HEV)	Vehicles^{2037}	HEV^{2037}	Gas^{2037}	$\Delta Vehicles$	Δ HEV	Δ Gas
1	11013	41	10972	0.72	12665	646	12019	1652	605	1047
2	15093	113	14980	1.99	17357	1784	15573	2264	1671	593
3	18100	174	17926	3.05	20815	2735	18080	2715	2561	154
4	20072	251	19821	4.42	23083	3963	19120	3011	3712	-701
5	22312	356	21956	6.25	25659	5604	20055	3347	5248	-1901
6	25896	491	25405	8.63	29780	7738	22042	3884	7247	-3363
7	28177	713	27464	12.55	32404	11253	21151	4227	10540	-6313
8	28658	859	27799	15.11	32957	13549	19408	4299	12690	-8391
9	30005	1161	28844	20.44	34506	18328	16178	4501	17167	-12666
10	29998	1526	28472	26.85	34498	24075	10423	4500	22549	-18049
	229324	5685	223639	100.01	263723	89665	174056	34399	83990	-49591

Data in columns 1–5 based on 2017 NHTS vehicle level survey aggregated to households, by authors' household expenditure deciles. Data in columns 6–7 based on 2037 stock of HEV and Gas vehicles according to authors' forecast, assuming constant distribution of HEVs across expenditure deciles.

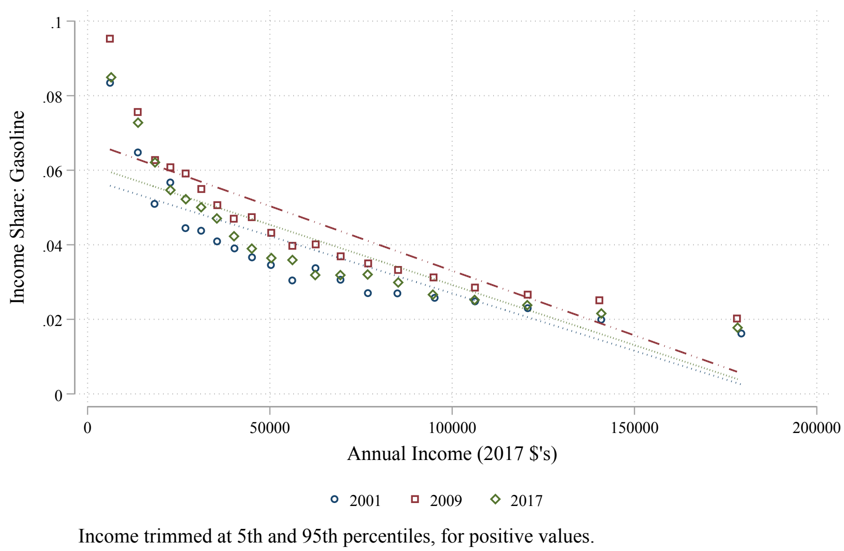
Table 9: Crosswalk from BEA's Total Requirements to CEX Expenditure Categories

BEA IO Commodity	CEX Category	Truck transportation Share
All other food and drinking places	food away from home	0.0070593
Amusement parks and arcades	fees and admissions	0.0090132
Automotive equipment rental and leasing	vehicle rental, leases, licenses and other charges	0.0043736
Automotive repair and maintenance	vehicle maintenance and repairs	0.0077437
Book publishers	reading	0.0110228
Child day care services	education	0.0078640
Civic, social, professional, and similar organizations	cash contributions	0.0070915
Clothing and clothing accessories stores	apparel and services	0.0090630
Direct life insurance carriers	life and other personal insurance	0.0009194
Dry-cleaning and laundry services	household operations	0.0094253
Elementary and secondary schools	education	0.0054672
Food and beverage stores	alcoholic beverages	0.0108911
Food and beverage stores	food at home	0.0108911
Full-service restaurants	food away from home	0.0093778
Gasoline stations	gasoline, other fuels, and motor oil	0.0154538
General merchandise stores	household operations	0.0099524
Grantmaking, giving, and social advocacy organizations	cash contributions	0.0048319
Health and personal care stores	personal care products and services	0.0055965
Health and personal care stores	drugs	0.0055965
Health and personal care stores	medical supplies	0.0055965
Home health care services	medical services	0.0052707
Hospitals	medical services	0.0072299
Independent artists, writers, and performers	fees and admissions	0.0008481
Insurance carriers, except direct life	vehicle insurance	0.0010972
Insurance carriers, except direct life	health insurance	0.0010972
Junior colleges, colleges, universities, and professional schools	education	0.0053413
Limited-service restaurants	food away from home	0.0116851
Medical and diagnostic laboratories	medical services	0.0050679
Motor vehicle and parts dealers	vehicle purchases	0.0112025
Museums, historical sites, zoos, and parks	fees and admissions	0.0070809
Newspaper publishers	reading	0.0065464
Nonstore retailers	household operations	0.0072482
Nursing and community care facilities	medical services	0.0067906
Offices of dentists	medical services	0.0048821
Offices of other health practitioners	medical services	0.0044240
Offices of physicians	medical services	0.0033476
Other ambulatory health care services	medical services	0.0080157
Other amusement and recreation industries	fees and admissions	0.0167363
Other educational services	education	0.0060345
Other personal services	household operations	0.0041878
Outpatient care centers	medical services	0.0050748
Owner-occupied housing	owned dwellings	0.0013106
Performing arts companies	fees and admissions	0.0044224
Periodical Publishers	reading	0.0080464
Personal and household goods repair and maintenance	household operations	0.0035449
Personal care services	personal care products and services	0.0053846
Religious organizations	cash contributions	0.0084143
Residential mental health, substance abuse, and other residential care facilities	medical services	0.0084259
Services to buildings and dwellings	natural gas	0.0091427
Services to buildings and dwellings	electricity	0.0091427
Services to buildings and dwellings	fuel oil and other fuels	0.0091427
Spectator sports	fees and admissions	0.0031418
Tenant-occupied housing	rented dwelllings	0.0004256
Veterinary services	pets	0.0130759
Waste management and remediation services	water and other public services	0.0307979
Wired telecommunications carriers	telephone services	0.0042030
Wireless telecommunications carriers (except satellite)	telephone services	0.0071040
Mean truck transportation cost share:		0.0072095

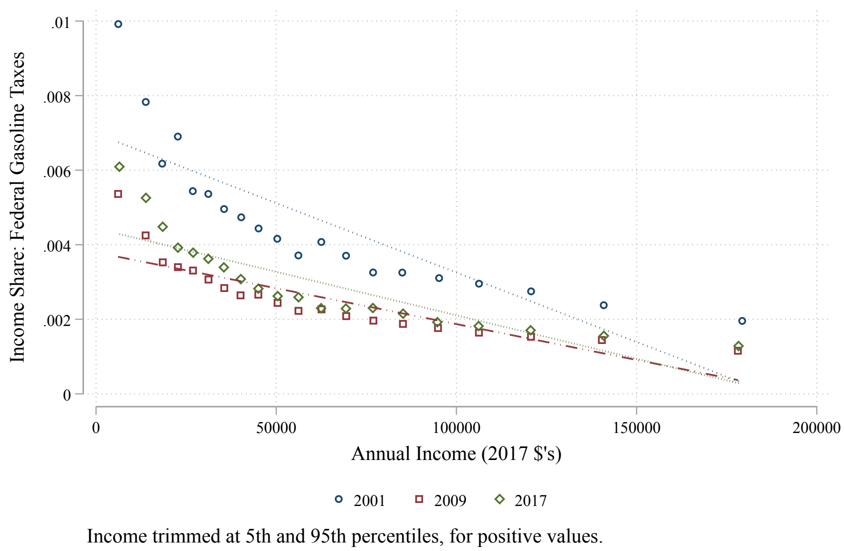
Notes: Data on total requirements from the BEA's total requirements table, for truck transportation industry (input) to all other commodities (output). Truck transportation share denotes the dollars of truckign industry input required, both directly and indirectly, to produce one dollar of the final BEA IO commodity for final use. Expenditure categories from the BLS's ***Table 1203.*** *Income before taxes: Annual expenditure means, shares, standard errors, and coefficients of variation, Consumer Expenditure Survey, 2019.* Crosswalked by authors.

B Appendix Figures

Figure 10: Gasoline and Federal Fuel Tax Expenditure Shares of Income in the CEX, by Income



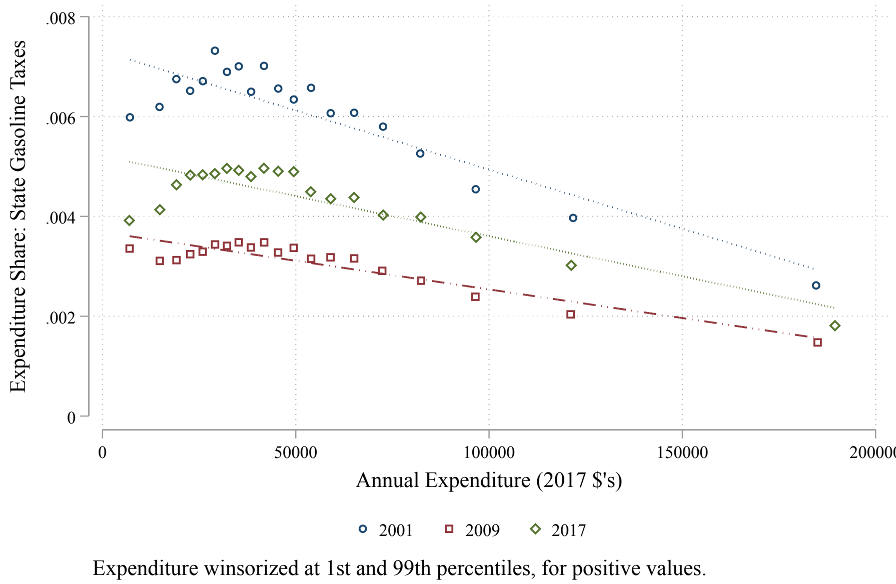
(a) Gasoline



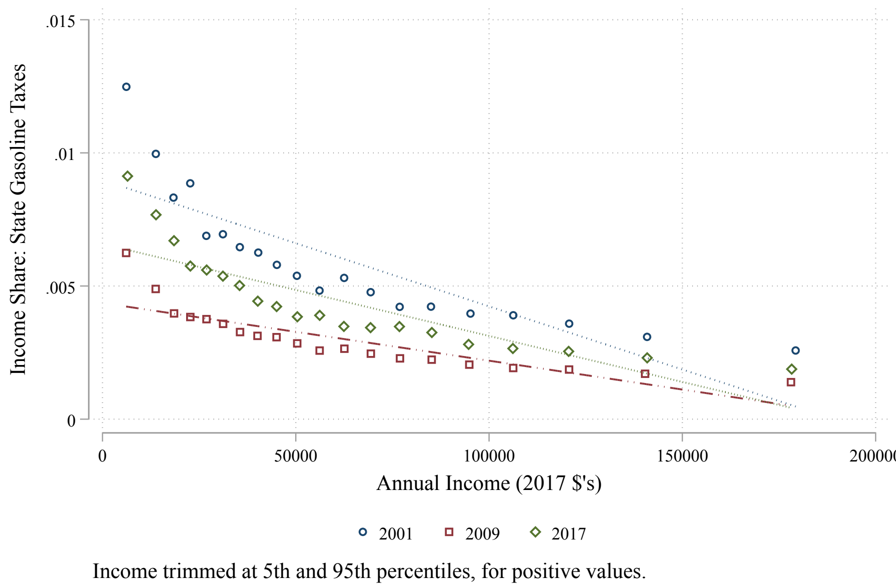
(b) Federal Taxes

Notes: Data from the CEX waves from 2001, 2009 and 2017. All panels plot binned scatters and their associated linear fits. Panel (a) shows the average income share devoted to gasoline expenditures by income ventile. Panel (b) plots the income share devoted to federal fuel taxes expenditures. Income is trimmed at the 5^{th} and 95^{th} percentiles prior to binning, for positive values of income. Data on annual fuel prices by state or region from the Energy Information Administration's "all grades all formulations" retail price average.

Figure 11: State Fuel Tax Expenditure Shares of Income and Total Expenditure in the CEX



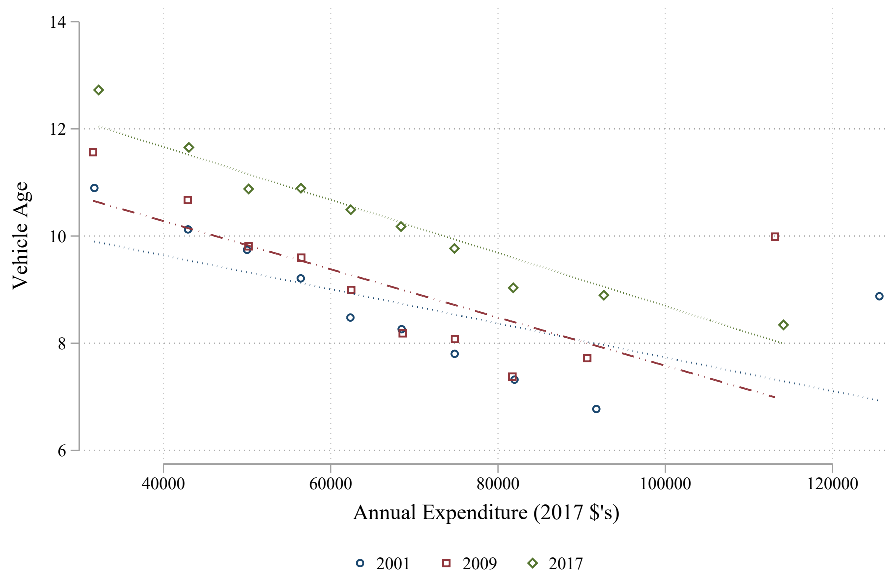
(a) Expenditure Share, by Expenditure



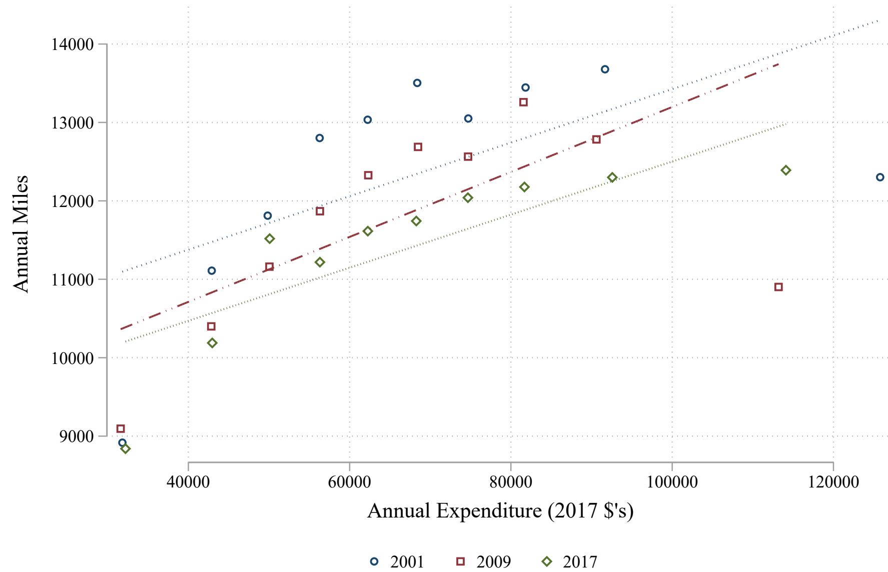
(b) Income Share, by Income

Notes: Data from the CEX waves from 2001, 2009 and 2017. All panels plot binned scatters and their associated linear fits. Panel (a) shows the average income share devoted to state gasoline taxes by income ventile. Panel (b) plots the expenditure share devoted to state fuel taxes by expenditure ventile. Income is trimmed at the 5^{th} and 95^{th} percentiles prior to binning, for positive values of income. Expenditure is winsorized at the 1^{st} and 99^{th} percentiles, prior to binning, for positive values of expenditure. Data on annual fuel prices by state or region from the Energy Information Administration's "all grades all formulations" retail price average. State motor fuels tax rates data come from the Brookings-Urban Tax Policy Center

Figure 12: Vehicle Characteristics in the NHTS, by Expenditure Level



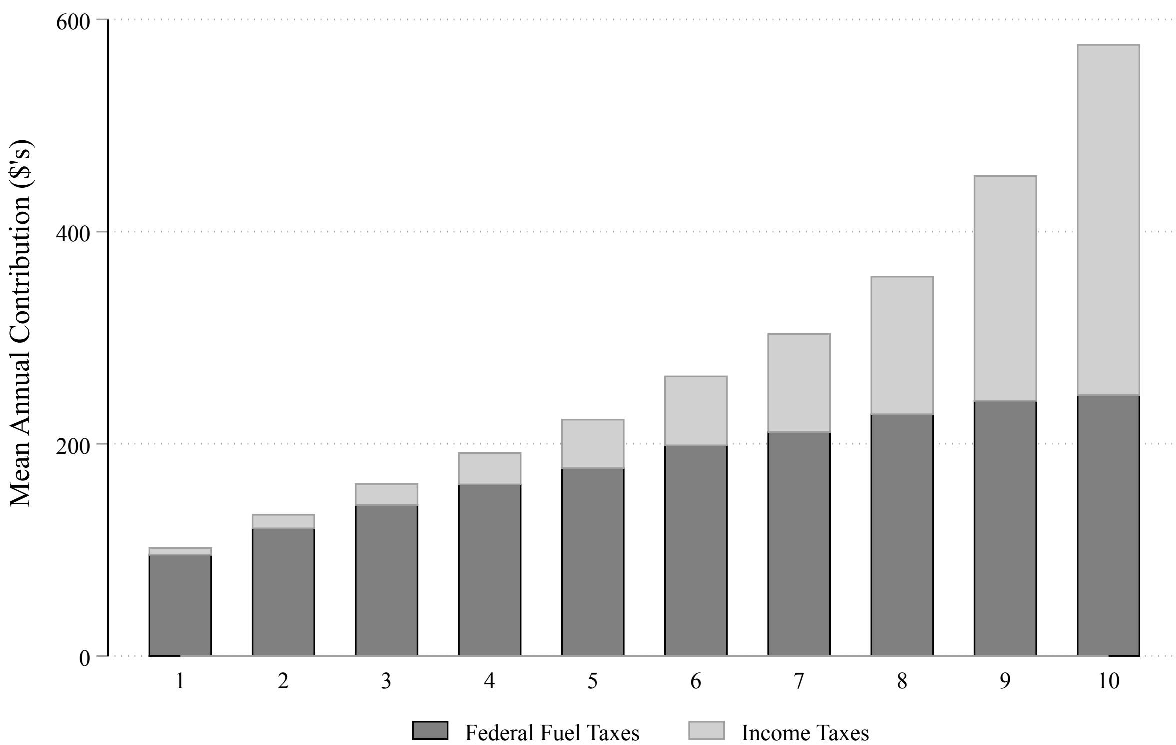
(a) Vehicle Age



(b) Miles Driven

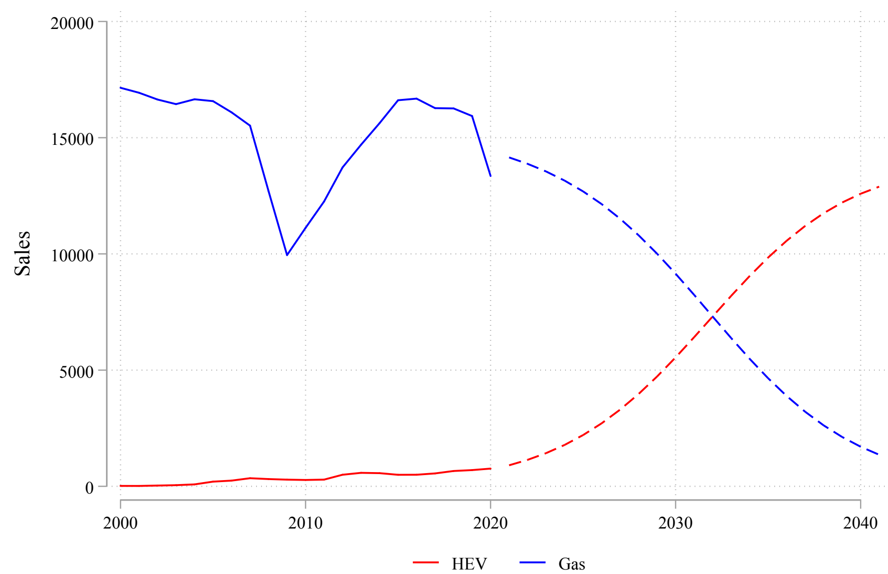
Notes: Data from the NHTS waves from 2001, 2009 and 2017. All panels plot binned scatters and their associated linear fits. Panel (a) shows the mean vehicle age by expenditure ventile. Panel (b) plots the average annual miles driven by expenditure ventile. Expenditure is winsorized at the 1^{st} and 99^{th} percentiles before binning, for positive values of expenditure.

Figure 13: Breakdown of Contributions to Highway Trust Fund (2017)

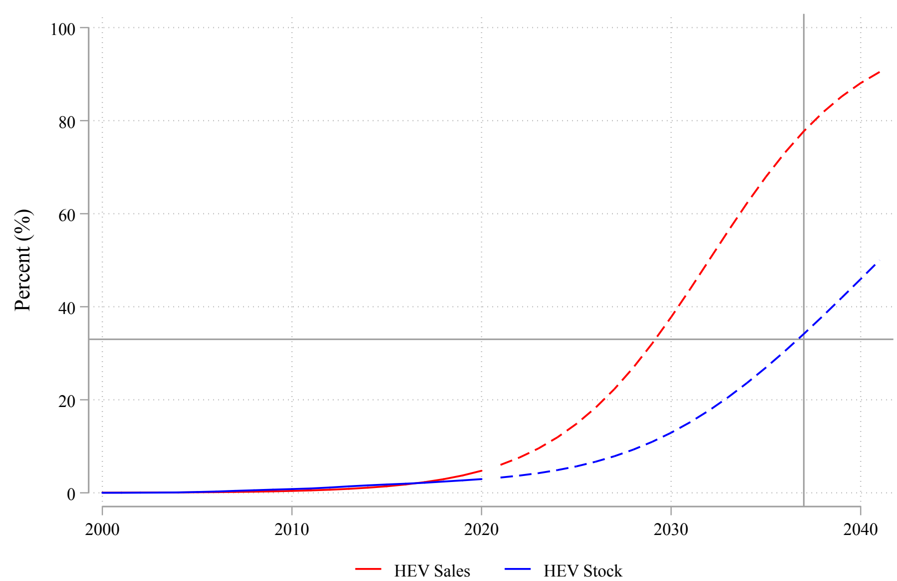


Notes: Data from the 2017 NHTS. Graph shows the annual household contribution to the HTF from federal fuel taxes, or from income taxes. Income taxes calculated using data from the NHTS in conjunction with the NBER's TAXSIM program.

Figure 14: Hybrid and Electric Vehicle Adoption Curves



(a) Sales



(b) Share

Notes: Data on vehicle registrations and sales by fuel type from *Transportation Energy Data Book, Edition 39* produced by Oak Ridge National Laboratory for the Department of Energy. Sales and share hybrid/electric based on data up to 2020; registration data through 2019. Additional years authors' forecast. Registrations, sales, and retirement in 1000's.