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The Distributional Impacts of a VMT-Gas Tax Swap

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Abstract

More stringent fuel economy standards and increased market penetration of electric vehicles (EVs) present challenges to federal policy makers who historically have relied on motor vehicle fuel excise taxes to fund highway projects. This paper considers the distributional implications of a federal tax swap where a new vehicle miles travelled (VMT) tax is used to finance a reduction in the federal excise tax on gasoline. Using data from the 2017 National Household Travel Survey (NHTS), I find this revenue neutral tax swap to be mildly progressive over most of the income distribution. The progressivity of the tax swap increases as fuel economy standards are raised and EV market penetration increases. In addition, I find the tax swap benefits rural drivers and has no discernable impacts on Black and Hispanic households.

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I. Introduction

Electric Vehicles (EVs) are increasingly popular and a major focus for policy makers as they consider ways to decarbonize the transportation sector. General Motors has announced that it will roll out 30 EV models globally by 2025 as part of its plan to move to an "all-electric future."[1] One fiscal concern with the shift from the internal combustion engine (ICE) to electric engines is its impact on motor vehicle fuel excise tax collections at the federal and state level. The federal excise tax has historically been the major source of funding for the Highway Trust Fund. But increased fuel economy in ICEs (see Figure 1) combined with the political challenges of raising the federal fuel excise tax rate has led to shortfalls in revenue for the trust fund. Greater penetration of EVs in the marketplace only exacerbates the problem (Figure 2). Federal motor transportation excise tax revenue is expected to be unchanged in nominal terms between 2017 and 2026; in real terms, the revenue is falling at the rate of between 1 and 2 percent per year.[2]

One solution is to shift from a gas tax to a vehicle-miles-traveled (VMT) tax. Besides addressing the problem of a shrinking tax base for the current fuel excise tax, a VMT tax is better aligned with the externalities created by driving. Research by Parry and Small (2005) shows that the lion's share of damages related to driving are driving-related damages (congestion, accident externalities) rather than fuel-related pollution. Two states, Utah and Oregon, have dipped their toes in the water. Oregon, for example, launched a voluntary pilot VMT tax in 2015 and is debating a mandatory VMT tax on new vehicles with a fuel economy of 30 MPG or higher to go into effect in 2026 (Duncan, 2021).

Opponents of a VMT tax raise several objections. First, a VMT tax requires collecting information on miles traveled; this raises privacy and data security concerns for many. Related are the

[1] See GM announcement at https://www.gm.com/electric-vehicles.html, accessed Oct. 7, 2021.
[2] Transportation excise tax revenue from Table 2.4 of the Historical Tables in Office of Management and Budget (2021).

administrative and compliance costs of collecting this information, sending out tax bills, and ensuring payment of the tax. The American Transportation Research Institute (2021) estimates that the administrative costs of a national VMT could exceed $20 billion annually. Environmentalists have also raised concerns. A VMT tax that replaced a motor vehicles fuel excise tax would remove an implicit subsidy to electric and hybrid vehicles and thereby discourage the greater electrification of the vehicle fleet.

Finally, there are fairness concerns. A VMT tax would be regressive, it is argued, and would unfairly burden low-income and rural drivers. As a recent Grist article notes, "Like the gas tax, and like sales taxes in general, a VMT tax would be regressive if applied uniformly across income brackets: It would take a larger percentage of income from low earners than it would take from high earners… A VMT tax would also be likely to disadvantage rural communities, as well as communities of color generally" (Mahoney, 2021).

This paper addresses this fairness concern. I analyze the distributional impact of a revenue neutral tax swap where a VMT tax is implemented with revenues used to lower (or eliminate) the excise tax on motor vehicle fuels. I focus on personal transportation rather than commercial transportation and trucking. Light duty vehicles accounted for 89 percent of vehicle miles traveled in 2018, according to the Federal Highway Administration's *Highway Statistics 2018* (Table VM-1). Some of this vehicle use is for commercial purposes; one estimate is that household based VMT accounts for 77 percent of total VMT.[3] In addition, it is not clear how to apportion commercial diesel tax burdens to households.

The next section of this paper surveys the literature on the distributional impact of VMT taxes. In a subsequent theory section, I demonstrate that a revenue neutral tax swap that used VMT tax revenues to replace some portion of gas tax revenues is progressive (regressive) if the income elasticity

[3] Figure 1-1 in *2017 NHTS Data User Guide*, available at https://nhts.ornl.gov/assets/NHTS2017_UsersGuide_04232019_1.pdf.

of the demand for fuel intensity (the reciprocal of fuel efficiency) is negative (positive). The following section presents regressions on the household demand for vehicle fuel intensity using data from the 2017 National Household Travel Survey (NHTS). Results indicate that the income elasticity of demand for fuel intensity is about -0.02.

I then test the theory by calculating the change in tax burden from a revenue neutral VMT Gas tax swap using the NHTS data and find that the swap is modestly progressive. This result holds using both an annual income measure and an approach that proxies for permanent or lifetime income. Next, I consider a simulation where fuel economy standards are increased by 40 percent and EV market penetration rises to 15 percent, reflecting the Biden Administration's initiatives to tighten fuel economy standards and incentivize greater purchases of EVs. In this counterfactual world, the VMT-gas tax swap is significantly more progressive. Finally, I present results showing that rural areas of the country benefit from the tax swap and that there do not appear to be any racial or ethnic differences in the impact of the tax swap. A concluding section suggests policy implications and suggestions for further research.

II. Background

While a number of papers have assessed various policies involving hybrid and electric vehicles as well as optimal tax rates for a VMT tax (see, for example, Davis and Sallee (2019), Zhao and Mattauch (2021), and Rapson and Muehlegger (2021)), few recent papers have looked at the distributional implications of a shift from a gas tax to a VMT tax. McMullen et al. (2010) simulates a tax swap for Oregon drivers based on data from the 2001 National Household Travel Survey (NHTS). They find the tax swap to be regressive. It is not clear that their study's results will hold up today given the overall increase in vehicle fuel economy and the increased market penetration of hybrid, plug-in hybrid, and electric vehicles (see Figures 1 and 2). Another study by Langer et al. (2017) compares and contrasts the efficiency and political grounds. While not a tax swap analysis, their paper provides evidence to

support a VMT-gas tax swap on efficiency grounds.[4] Weatherford (2012) notes several early papers that have compared VMT and gas taxes and concludes that the research "has not arrived at a strong consensus regarding whether [VMT taxes] would be more or less regressive than the [fuel] tax" (p. 23). He notes that the studies he surveys finds that rural drivers would benefit from the tax swap while urban drivers would not. In his own research using data from the 2001 and 2009 NHTS, Weatherford finds a VMT-gas tax swap would be distributionally neutral. He finds that it would reduce (increase) the tax burden for rural (urban) drivers. As noted above, EV and PHEV market penetration and fuel economy have both increased significantly between 2009 and 2017, suggesting the value of revisiting this question with more recent data.

III. Theory

Individuals derive utility from travel (M), measured in vehicle miles traveled, fuel intensity (E), measured in gallons per 1000 miles traveled, and a vector of vehicle attributes (A).[5] Maximizing utility subject to a budget constraint yields demand equations for these three driving related goods:

$$M = M(p_M, Y, X_M)$$

$$E = E(p_F, Y, A, X_E)$$

$$A = A(p_A, Y, X_A)$$

where $p_M, p_F, \text{and } p_A$ are the price of driving a mile, the price of fuel, and the price of vehicle attributes, respectively. I can reduce this model to two equations by substituting the vehicle attributes equation into the fuel economy equation:

$$M = M(p_M, Y, X_M)$$

$$\hat{E} = \hat{E}(p_F, Y, X_{\hat{E}}).$$

[4] They also carry out a distributional analysis of sorts, but it compares a VMT tax with differentiated rates between urban and rural drivers with a uniform gasoline tax. It is not clear if it the tax swap or differentiated rate structure for the VMT tax that drives their results.

[5] With some modification, this approach follows Small and Van Dender (2007a).

Making this substitution means that any income elasticity of demand for fuel intensity is one where we are *not* controlling for vehicle attributes. I flag this because many studies measure fuel intensity income elasticities controlling for vehicle attributes. But for the purposes of assessing the distributional consequences of a shift from a gasoline to a VMT tax, the income elasticity that matters is the one from this latter fuel economy equation.

The price of driving a mile is defined as

$$p_M = p_F E + t_M,$$

where the price of fuel is tax inclusive and t_M is the VMT tax rate (currently zero).[6] The demand for gasoline is a derived demand from the demand for VMT and fuel intensity:

$$F = M \cdot \hat{E}$$

and income elasticities are related as

$$\eta_F = \eta_{\hat{E}} + \eta_M.$$

To emphasize, I do not want to control for vehicle attributes when estimating an income elasticity of fuel economy. In considering a revenue neutral shift from a gas tax to a VMT tax, the variation in the demand for fuel intensity over income should allow for the correlation between vehicle attributes and income. Going forward, I will refer to fuel economy as E but I have in mind fuel economy where income can affect fuel intensity through changes in the demand for attributes ($\hat{E}$).

Define driving related tax revenue as $R = t_M M + t_F F$ where the first term is the VMT tax and the second term is gasoline excise revenue. I will consider a policy change where the VMT tax rate is increased (from zero) and the tax rate on gasoline reduced to keep total revenue constant:

$$\frac{dR}{dt_M}\Big|_{t_M=0} = \sum_i \frac{dR_i}{dt_M} = \sum_i \left(M_i + \frac{dt_F}{dt_M}\left[F_i + t_F \frac{\partial F_i}{\partial t_F}\right]\right) = 0, \quad (1)$$

[6] The relevant price per mile is a marginal price and also includes the depreciation and repair costs per mile driven. Excluding these additional costs will not affect my results as none of my analysis requires a percentage change in price but rather the absolute price change. A tax swap changes the tax-inclusive price of fuel and the VMT tax rate but has no effect on these other elements of the price per mile.

where i is indexing over households.[7] The term $\frac{dt_F}{dt_M}$ measures the revenue neutral change in the gas tax rate relative to the new VMT tax rate. This term is constant across all individuals and, presumably, is negative starting from a zero tax rate on VMT. Call this term δ. I can rewrite equation as

(1') $$\frac{dR}{dt_M} = \sum_i \frac{dR_i}{dt_M} = \sum_i \left(M_i + \delta F_i \left[1 + \frac{t_F}{p_F} \frac{p_F}{F_i} \frac{\partial F_i}{\partial t_F} \right] \right) = 0,$$

or

(2) $$\frac{dR}{dt_M} = \sum_i \frac{dR_i}{dt_M} = \sum_i (M_i - \psi F_i) = 0$$

where

$$\psi = -\delta(1 + \theta_F \varepsilon_{FF}),$$

θ_F is the excise tax rate divided by the tax-inclusive price of fuel, and ε_{FF} is the own price elasticity of demand for fuel. The term in parentheses is positive so long as an increase in the tax on gasoline increases gas tax revenue (i.e., no Laffer effect). I will assume that condition holds. Since $\delta < 0$, $\psi > 0$. The units for ψ is miles per gallon. Let $\bar{E} = \frac{1}{\psi}$. If the price elasticity of demand for fuel is constant across all households, then $\bar{E}$ is a threshold level of fuel intensity such that

$$\frac{dR_i}{dt_M} > 0 \text{ for } E_i < \bar{E}$$

and

$$\frac{dR_i}{dt_M} < 0 \text{ for } E_i > \bar{E}.$$

In words, drivers with low fuel economy cars ($E_i > \bar{E}$) pay less in driving related taxes with this tax shift while drivers with high fuel economy cars ($E_i < \bar{E}$) pay more. Whether the tax shift is progressive (relative to the pivot point) or not depends on the sign of the income elasticity of demand for fuel

[7] Households may own more than one vehicle. The term dR_i is the change in tax revenue per vehicle. In the distributional analysis, I'll sum revenue changes over vehicles to the household level.

intensity (η_E). If it is negative (higher income households demand more fuel efficient cars), then the tax shift is progressive around the pivot point. Conversely, if it is positive, then the tax shift is regressive around the pivot point.

While information relative to the pivot point is useful, it does not really tell us anything about global progressivity. Economists say that a tax is progressive (regressive) if the average tax rate defined as the tax payment relative to some measure of income rises (falls) with income.[8] Most studies find the current gas tax to be regressive (see, for example, West and Williams, 2004).[9] Whether the gas tax is regressive or not is, to a large degree, irrelevant for the question at hand. What matters is the *relative* regressivity of each tax. To assess the impact of a VMT-gas tax swap, we need to measure the change in the average tax rate (ATR) as the reform is implemented:

$$\frac{dATR_i}{dt_M} = \frac{d\frac{R_i}{Y_i}}{dt_M} = \frac{M_i - \psi F_i}{Y_i}. \tag{3}$$

Whether the tax swap is progressive or not depends on the sign of the derivative of the change in the ATR with respect to the reform as income changes:

$$\frac{\partial\left(\frac{dATR_i}{dt_M}\right)}{\partial Y}\begin{cases} > 0 & progressive \\ < 0 & regressive \end{cases}$$

A formula for this derivative is given by

$$\frac{\partial\left(\frac{dATR_i}{dt_M}\right)}{\partial Y} = \frac{M_i - \psi F_i}{Y_i^2}\left\{(\eta_M - 1) - \left(\frac{\psi F_i}{M_i - \psi F_i}\right)\eta_E\right\}. \tag{4}$$

[8] How one measures income is a long-standing topic of study in economics. A snapshot measure of income may misrepresent the taxpayer's true resources. Economists have used various proxies for lifetime or permanent income. See Fullerton and Metcalf (2002) for more on this issue.

[9] Studies using lifetime income proxies (e.g. current consumption as in Poterba, 1991) find much less regressivity. Teixidó and Verde (2017), however, argue that findings such as Poterba's ignore important wealth effects that mask regressivity.

Consider first those households with high fuel intensity vehicles ($M_i - \psi F_i < 0$). Based on the analysis of Small and Van Dender (2007b), the income elasticity of VMT is less than 0.6.[10] If $\eta_E < 0$, the change in the average tax rate rises with income:

$$(4') \qquad \frac{\partial\left(\frac{dATR_i}{dt_M}\right)}{\partial Y} = \underbrace{\frac{M_i - \psi F_i}{Y_i^2}}_{<0}\left\{\underbrace{(\eta_M - 1)}_{<0} - \underbrace{\left(\frac{\psi F_i}{M_i - \psi F_i}\right)}_{<0}\underbrace{\eta_E}_{<0}\right\} > 0.$$

The tax reform is strictly progressive over the range of fuel intensity such that the average tax rate is falling. Conversely, if $\eta_E > 0$, the sign depends on the relative magnitude of the two terms in the braces. For high fuel intensity cars (high value of E_i), the first term will dominate and the derivative will be positive. As E_i approaches $\bar{E}$, the second term will dominate and the sign of this derivative will become negative.

Now consider those cars with low fuel intensity ($M_i - \psi F_i > 0$). If $\eta_E < 0$, the sign of the derivative is ambiguous:

$$(4'') \qquad \frac{\partial\left(\frac{dATR_i}{dt_M}\right)}{\partial Y} = \underbrace{\frac{M_i - \psi F_i}{Y_i^2}}_{>0}\left\{\underbrace{(\eta_M - 1)}_{<0} - \underbrace{\left(\frac{\psi F_i}{M_i - \psi F_i}\right)}_{>0}\underbrace{\eta_E}_{<0}\right\}.$$

For values of E_i close to $\bar{E}$, the denominator of the fraction in the curly braces is close to zero and the second term dominates. In that case

$$\frac{\partial\left(\frac{dATR_i}{dt_M}\right)}{\partial Y} > 0, \qquad \text{for } E_i \text{ near } \bar{E}.$$

[10] See appendix for calculations.

But as fuel economy grows, the second term in the curly braces gets smaller and at some point the first term dominates in which case the change in the average tax rate begins to fall with income. EVs are at the limit where $E_i = F_i = 0$ and

$$\frac{\partial\left(\frac{dATR_i}{dt_M}\right)}{\partial Y} = \frac{M_i}{Y_i^2}(\eta_M - 1) < 0.$$

There is no incentive to increase fuel efficiency further to avoid gasoline consumption since it has already been driven to zero. Driving increases with income but at a slower rate so that the average tax rate falls.

If $\eta_E > 0$, the derivative then is negative. The change in the average tax rate falls with income. Figure 3 sums up the results for the two different cases (positive or negative income elasticity of fuel intensity). If the income elasticity is negative, the change in the ATR is negative at low levels of income but approaches zero. At the point where the change in the ATR equals zero, the slope of the curve is positive. Eventually the curve peaks and the change in the ATR for higher values of income begins to fall. If the income elasticity of fuel intensity is positive, the change in the ATR is positive at low levels of income but falls towards zero. At the point where the change in ATR equals zero, the slope is still negative. The change in the ATR eventually reaches a minimum and then begins to rise as income grows.

Figure 3 makes the point that the VMT-gas tax swap is progressive over much of the income range if the income elasticity of fuel intensity is negative. Conversely, it is regressive if the elasticity is positive. The next section addresses this issue by estimating the income elasticity of fuel intensity.

III. Estimating the Income Elasticity of Fuel Intensity

I use data from the 2017 National Household Travel Survey (NHTS) for the empirical analysis in this paper. The NHTS is a stratified random sample of households in all fifty states and asks questions about travel behavior and all modes of travel. The survey was conducted from March 2016 through

May 2017. It collects information about the household, all residents of the household, all motor vehicles owned, and detailed information about trips taken during a designated 24 hour period.[11] The survey is designed to collect information about daily travel, whether for commuting, errands, vacation, or other household trips. According to the User's Guide, household based travel in light-duty vehicles accounted for 77 percent of vehicle miles traveled (VMT).

The data are reported in several files: household, person, vehicle, and trip. There are 129,696 households included in the survey and 256,115 vehicles included in the vehicles file. Household weights are assigned to allow population-level estimates for the household and vehicles file. Separate person weights are assigned for the persons file. Households are included in the sample whether they own motor vehicles or not. Of the 129,696 households surveyed, 6,249 do not own vehicles (4.8 percent of households). All households that own vehicles are included in the vehicles data file. I use data from the vehicles file. For the welfare analysis (described below), I aggregate vehicles up to the household level to calculate total miles driven and fuel consumed.

In the analysis, I restrict attention to light-duty vehicles (cars, vans, SUVs, pickup, and other trucks), reducing the sample by 12,209 observations.[12] I also drop households with more than 5 vehicles (following Levinson, 2019) or households with missing income as well as vehicles with no annual mileage reported or whose mileage has been flagged by NHTS as an outlier. Finally, I drop vehicles in the top and bottom 0.5 percentile of annual mileage. The final sample has 208,168 vehicles (see Table 1).

The 2017 NHTS adjusts the EPA fuel economy ratings used for the Corporate Average Fuel Economy (CAFE) standards by accounting for actual driving conditions as opposed to test lab

[11] Detailed information about the 2017 NHTS is available at https://nhts.ornl.gov/.
[12] Other trucks are defined in the User Guide Glossary as "all trucks other than pickup trucks (e.g., dump trucks, trailer trucks, etc.)." Note that they are all privately owned. I include these vehicles 1,414 vehicles as analysis of the trip data indicate that 83 percent of the trips made with these vehicles are non-work related (variable whytrp1s).

conditions.[13] I construct a fuel intensity measure as 1000/mpg where mpg is the NHTS reported fuel economy rating. This fuel intensity variable measures gallons per 1000 miles travelled. For EVs, the fuel economy rating is the miles per gallon equivalent, the amount of electricity equivalent to a gallon of gasoline. Given my focus on a VMT-gas tax swap, I set the fuel intensity measure for EV's equal to zero. For plug-in hybrids, two fuel economy measures are reported. One measure is the miles per gallon when operating only on gasoline. The other is a miles per gallon equivalent as with EVs. Since I don't know what proportion of driving is done on battery as opposed to gasoline, I carried out the analysis assuming either 0 or 100 percent battery use. In the paper, I provide results assuming 100 percent battery use. Results are not appreciably changed by assuming 0 percent battery use.

The NHTS does not measure actual fuel consumption. Rather it estimates fuel consumption for each vehicle as annual miles driven divided by the fuel economy rating. I compute fuel consumption as annual miles traveled times my fuel intensity variable described above. Thus, while the NHTS reports positive fuel consumption for EVs, I set their consumption to zero (as well as consumption for PHEVs in one scenario as discussed above).

Table 2 reports annual average mileage, fuel consumption, and fuel intensity for the vehicles included in the data set. Overall, the average fuel intensity is 49.1 gallons per 1000 miles (20.4 miles per gallon), ranging from 0 to 167. The average VMT is 10,517 miles and average fuel consumption is 507 gallons per vehicle per year. While the maximum fuel consumption in the data set is over 5000 gallons, this is a significant outlier. The 99th percentile of fuel consumption is 1,758 gallons. Cars make up just half of the vehicles in the data. They have lower average fuel intensity (42.0 gallons per 1000 miles) but are driven roughly the same distance. Vans, accounting for 5 percent of the vehicles, use more fuel per

[13] EIA adjusts the EPA measures down by roughly 15 percent to account for differences between actual driving and testing lab performance. They then make a further adjustment to account for vehicle driving patterns (e.g. short trips use more fuel) and seasonal weather conditions by location. The methodology is described in greater detail in the 2009 NHTS documentation: https://nhts.ornl.gov/2009/pub/DerivedAddedVariables2009.pdf.

mile and are driven slightly more than vehicles on average. As a result, they use about 17 percent more fuel than vehicles on average. Sport Utility Vehicles (SUVs) account for one-quarter of the vehicle stock in the dataset and, like vans, use more fuel and are driven slightly more than vehicles on average. Finally, pickup trucks account for a little under one-fifth of the vehicles and use considerably more fuel (64.3 gallons per 1000 miles) but are driven a bit less than vehicles overall.

Table 3 reports summary statistics on the 113,434 households with vehicles that are included in the analysis. The NHTS reports income by bins. I set household income equal to the midpoint of each bin and equal to $300,000 for the top bin ($200,000 or more). Mean household income with my constructed measure is $81,189. In the analysis below, I use both my constructed income variable and the income bins for distributional analyses. The average household size is just over 2.5. A little over one-third of the homes have children in them. Must adults drive in a household and two-thirds of the households are in owner occupied housing.

Driving depends on density patterns in the area. I include a number of controls including whether the household is in an urban area as well as whether the block in which the household resides is an urban or rural block group (other possible block group types are second city, suburban, and small town).[14] I also have a measure of population density for the household's block group. Having multiple measures of urban density accounts in a more flexible way for the various driving patterns different households might experience.

Finally, we include information at the household level on vehicles. The average fuel intensity of household vehicles (weighted by vehicle miles traveled) is 48 gallons per 1000 miles (21 miles per gallon)

[14] Block groups comprise 600 to 3,000 people and are the smallest geographic units tabulated in sample data. Urban areas are larger geographic clusters with 2,500 or more people (depending on the type of urban area). See https://www.census.gov/content/dam/Census/data/developers/geoareaconcepts.pdf for more on census designations.

and the average household driving is just under 20,000 miles a year with average fuel consumption of 934 gallons.

Table 4 presents results from regression of fuel intensity on household income and other variables. Regressions (1) and (2) are OLS regressions with and without additional household control variables. The next two regressions add state level fixed effects to control for unobserved state variables that could be correlated with income and the demand for fuel intensity.[15] In all cases, the coefficient on the log of household income is negative and statistically significant. Adding state fixed effects modestly reduces the magnitude of the semi-elasticity. Adding additional control variables nearly doubles the estimated semi-elasticity. Using the fourth regression in Table 4, the elasticity of fuel intensity with respect to income at the mean value of fuel intensity is -0.020. Income does appear to affect the demand for fuel intensity, but the effect is modest.

Figure 4 shows the impact of income on fuel intensity by graphing the estimated coefficients for income bins along with 95 percent confidence intervals. When additional regressors are excluded, there is a very modest downward trend in the impacts on fuel intensity as income rises (top panel). The impact is much more pronounced once other regressors are included (bottom panel). However, the difference in fuel intensity between the bottom and top of the income distribution is small – on the order of 3 gallons per 1000 miles (less than 10 percent of average fuel intensity).

My results stand in contrast to those of Levinson (2019). He finds a positive relation between income and fuel intensity using the 2009 NHTS in a regression where he does not control for any vehicle attributes (Table 5, column 2). The coefficient on income for this regression, however, becomes

[15] I also have run regressions at the household level where I regress various measures of household fuel intensity on income and other variables. The fuel intensity measures include an average over household owned vehicles, VMT weighted average fuel intensity, and fuel intensity of the vehicle with maximum VMT. In all cases the estimated coefficient on the income variable is negative and statistically significant.

negative if EIA's fuel economy measure is used rather than the EPA measure that Levinson used.[16] As noted above, the EIA measure takes into account real world driving conditions and vehicle use.

Using data from the Massachusetts Vehicle Census, Lu (2021) finds fuel intensity rises with income whether other vehicle attributes are controlled for in the regression or not (Table 2). His data, however, are for motor vehicles in model years 2011-2012 and there are few EVs or PHEVs in his dataset. As noted in Figure 2 below, these vehicles are only starting to enter the marketplace in 2011.

While it might be imagined that higher income households prefer more fuel intensive vehicles, the data suggest two countervailing forces. First, EV, PHEV, and hybrid vehicle ownership is positively correlated with income (albeit only modestly) either unconditionally or after controlling for the other household attributes included in Table 4.[17] Even setting aside hybrid or EV ownership, higher income households tend to own newer vehicles which, in turn, consume less fuel on average (in no small part due to more stringent fuel economy standards). A simple regression of fuel intensity on vehicle age indicates that cars consume 1.3 gallons per 1,000 miles more fuel for each year of age.[18]

Given the results in this section, I would expect the VMT-Gas tax swap to be progressive over most of the income distribution (see top panel of Figure 3). In the next section, I turn to that empirical analysis after first defining my measure of welfare.

IV. Distributional impacts of the tax reform

A theoretically rigorous measure of the welfare impact of a VMT-gas tax swap would measure the equivalent (or compensating) variation at the household level and then compare across income levels. To do this, I would need to assume a functional form for utility (or equivalently the expenditure

[16] I am grateful to Arik Levinson for sharing his data and STATA code with me.
[17] Unconditional correlation coefficients range from .04 to .06.
[18] A simple quadratic regression yields $\hat{E} = 39.5 + 1.32A - .023A^2$, with all p-values essentially zero. At the median vehicle age (9 years), the slope of fuel intensity with respect to age is 0.9 gallons per 1000 miles.

function). However, it is not necessary to do that. As I argue in the appendix, the welfare impact is reasonably well approximated by the change in tax burden:

$$\Delta W_i \cong -dR_i = -(t_M M_i + dt_F F_i) \quad (5)$$

where $t_M > 0$ is the revenue neutral VMT tax rate for a given reduction in the gasoline excise tax rate $(dt_F < 0)$. I will report the change in tax revenue as the measure of the welfare change for each household. While this underestimates the impact of the tax swap on individual households, it should not impart any bias to the distributional impact across income groups.

I calculate this measure of the change in welfare at the household level after first estimating the revenue neutral VMT tax rate for a ten cent per gallon reduction in the gasoline excise tax rate. A ten cent reduction in the gas tax reduces gas prices for drivers in the 2017 NHTS by 4 percent on average. Ignoring changes in driving behavior or fuel intensity (a static estimate), the revenue neutral VMT tax rate is 0.48 cents per mile. This lowers the price of driving per mile by 4 percent on average. On average the VMT gas tax swap collects $93 in VMT taxes per household while simultaneously lowering gas tax payments by the same amount. The standard deviation of the household change in tax payments is $23 and the tax change ranges from a reduction of $388 per household per year to an increase of $192.

Any distributional analysis where households are ranked by annual income suffers from the well-known measurement problem that annual income may differ significantly from a measure of permanent or lifetime income. Measurement error is also an issue, especially in lower income deciles where expenditures commonly exceed reported income. A measure of permanent or lifetime income more accurately welfare differences across households (e.g. Friedman, 1957). In their seminal work on measuring the U.S. tax burden, Pechman and Okner (1974) address the problem of high consumption to income ratios in lower income deciles by excluding the bottom half of the lowest income decile from their distributional analysis. Their approach was followed by subsequent researchers before economists

explored either using current consumption as a proxy for lifetime income (e.g. Poterba, 1991) on the argument that households do consumption smoothing over their lifetime, or explicitly measured lifetime income and taxes (e.g. Fullerton and Rogers, 1993).

I take two approaches to this problem of approximating household welfare by annual income. My first approach is to use annual income but exclude those households for whom gasoline expenditures exceed fifty percent of household income. This is admittedly an arbitrary cut-off, but distributional results are not appreciably affected by the choice of cut-off. Of the 113,307 households from the 2017 NHTS included in the welfare analysis, 534 households have gas expenditures in excess of fifty percent of household income – less than one-half of one percent of the sample. Of these households, 93 percent are in the lowest income group (household income less than $10,000) and the remaining 7 percent have income below $25,000.

Using annual income has its drawbacks but does accord with how most policy related distributional analyses are done in Washington DC. As an alternative (or supplementary approach), I limit my analysis to households with household heads between the ages of 40 and 60. The logic here is that annual income most significantly diverges from a lifetime income measure for those starting out in life and, perhaps, making significant human capital investments and for those who have (mostly) exited the workforce and are drawing down personal savings and pensions in retirement.

1. Annual Income Distributional Analysis

Table 5 presents results at the household level of a regression of the change in tax payments on the log of income along with other household level variables. The change in tax payments is positively correlated with income in all four of the regressions. Controlling for other household covariates is clearly important for estimating the income effect on the change in tax payments. In both sets of regressions (with and without state fixed effects), adding other covariates leads to larger coefficients on

the income variable. Focusing on the regression with covariates and state level fixed effects, the change in tax payments rises by a little under one penny for each one percent increase in income.

Figure 5 graphs the estimated coefficients from the same regression as in Table 5 but with income bin variables rather than the log of income. I only show the figure for the regression including other covariates and state fixed effects. Results are noisier when other covariates are excluded; but similar when covariates are included but state fixed effects are excluded. Two things stand out in this table. First, the average change in tax payments is initially negative in the lowest income group but rises nearly monotonically across the income groups. Second, the average change in tax payments is quite modest – ranging from a little more than a one dollar decline for the lowest income group to a little more than a two dollar increase in the highest income group. This range corresponds to approximately 6 percent of the average fuel tax, pre-reform.

While the average change in taxes is quite small, there is heterogeneity within the income groups. Figure 6 shows what percentage of households pay more in taxes (top panel) and what percentage pay at least $50 more in taxes (bottom panel). Roughly half the households in each income group pay more in taxes, with the percentage rising slightly with income. Few households (less than 5 percent) pay $50 or more in additional taxes as a result of the tax swap. The percentage is under one percent for the lowest income group and rises to just over four percent for the highest income group.

2. Lifetime Income Distributional Analysis

Next I report results for households with heads of household between the ages of 40 and 60 as a way to address the problem that annual income may not be a good measure of lifetime income for households starting careers or entering retirement. Limiting households in this way removes some of the difference between income on which consumption decisions are being made and measured income. It does not address possible transitory income fluctuations, but it would be difficult with the NHTS to deal with that issue given the single snapshot of income for households.

While "persons" are tracked within each household in the NHTS, there is no identifier for head of household. There can be as many as 13 persons in a single household though over 80 percent of households have only 2 people in them. Looking at the age distribution for the various person identifiers (personid), it is plausible to expect that most heads of household are being identified as person 1 or 2. The interquartile range and median age for person 1 is 45 to 69 with a median age of 59 while for person 2 is 39 to 66 with a median of 55. For every other person (3 – 13), the 75th percentile age is less than 25. For each household I record the age of person 1 and person 2 and create a lifetime income index variable based on one of three criteria: 1) the older person is between the ages of 40 and 60; 2) the younger person is between the ages of 40 and 60; and 3) both are between the ages of 40 and 60.[19] I report results using the first lifetime income index to select households for the analysis.[20]

Table 6 shows the results from a regression of the change in tax payments on income and other variables. If anything, the tax swap looks slightly more progressive than when all households are included in the analysis, a result commonly found in analyses of excise taxes when lifetime rather than annual income measures are used. The coefficient on the ln(income) variable in the fixed effects model with other covariates rises from 0.938 to 1.089. Figure 7 (top panel) shows the change in tax payments by income group from the state fixed effects regression with covariates. The same upward sloping pattern occurs as in Figure 5 (bottom panel) though the range between the first and last income group is now larger. The percentage of households with welfare decreases of $50 or more looks similar (Figure 6, bottom panel compared to Figure 7, bottom panel).

In summary, whether one uses all households or limits households to an age group likely to be near the peak of their lifetime earnings potential, a VMT Gas Tax swap appears to be modestly progressive. But the actual changes in welfare are quite small for nearly all households. This reflects

[19] If there is only one person in the household, I simply use the age of that person.
[20] Results are very similar no matter which criterion I use for selecting households. Results are available upon request.

that reality that personal driving gasoline taxes are a modest fraction of most households' income and that a VMT tax would also have small impacts on most households. Given average household driving of roughly 20,000 miles per year, a VMT tax set at one-half penny per mile would raise about $100 per household. This would be offset by a decline in the gasoline tax that, on average, would also equal about $100.

3. Distributional Analysis Assuming More Stringent Fuel Economy Standards and Greater EV Penetration

The analysis above is based on alternative fuel market penetration as of 2017. Innovation in the EV, PHEV, and Hybrid market is rapid and, as noted, major automobile manufacturers are committed to accelerating the shift to non-gasoline powered vehicles. At the same time, fuel economy standards for internal combustion engine powered vehicles continues to rise. The distributional implications of a VMT gas tax swap will likely look very different as more EVs, PHEVs, and more fuel efficient vehicles penetrate the market.

To assess the distributional implications of this alternative market structure, I assume EVs and PHEVs comprise 15 percent of the vehicle fleet and, following Langer, et al. (2017), increase fuel economy by 40 percent. The latter is consistent with the more stringent fuel economy standards initially put forward by the Obama Administration and subsequently reinforced by the Biden Administration.

To increase EV and PHEV market share, I run logit regressions of EV and PHEV ownership on a number of household variables.[21] For both regressions, income is the key determinant of EV and PHEV ownership (see appendix 5 for regressions). I use the predicted values from these regressions to simulate greater market penetration by assuming EV and PHEV ownership above a given threshold. This approach assumes households own the same number of vehicles and simply shifts vehicles from

[21] I also ran Probit regressions and the results are very similar.

internal combustion to either EV or PHEV.[22] EV and PHEV ownership is predominantly concentrated in upper income groups.

Higher fuel economy standards lower the price of driving per mile. This, in turn, can lead to more driving – a phenomenon known as rebound. A central estimate of the rebound effect is 10 percent (Gillingham, 2018), meaning 10 percent of the fuel savings from higher fuel economy standards is lost due to increased driving. Given a 40 percent increase in fuel economy, this implies vehicles are driven 4 percent more miles (see Appendix). I increase vehicle miles traveled by 4 percent for all vehicles and, based on the higher fuel economy standards, recompute gasoline consumption.[23]

Results from the simulation show a markedly more progressive result for the VMT gas tax swap. Table 7. The effect of income on the change in tax payments is an order of magnitude larger, reflecting in large measure the importance of income for driving EV and PHEV market penetration. Results are even more striking when income bin coefficients are plotted (Figure 8). The change in tax payments is negative but close to zero on average for households with incomes below $100,000. The change in tax payments becomes positive and steeply increasing with income approaching, on average, $80 per household (top panel). Almost two-thirds of households in the top income group see an increase in taxes of at least $50 (bottom panel). While not shown here, the change in the average tax rate is monotonically increasing with income through all but the top income group. However, even with the higher fuel economy and market penetration of EVs and PHEVs, the average tax rate change is modest ranging from -0.1 percentage point for the lowest income group to roughly 0.25 percentage points for households with income above $150,000.

[22] This paper version only uses household characteristics to predict EV and PHEV ownership. Therefore, it makes all vehicles for a given household either EV or PHEV (or conventional fuel). In future revisions, I'll revisit this approach.

[23] I also increase VMT by 4 percent for EVs and PHEVs. The literature on rebound for EVs is sparse. Davis (2019) actually finds that EVs are driven less than gasoline powered vehicles. But, as he acknowledges, this difference could be driven by sample selection among purchasers. Bauer (2018), in contrast, finds a modest increase in driving among Norwegian drivers.

The simulation suggests that the case for a VMT gas tax swap becomes more compelling on distributional grounds in addition to revenue grounds as overall fuel economy standards are raised and EV penetration gains steam.

V. Other Distributional Considerations

Policy makers care about more than the income related distributional impacts of tax reform. In this section, I consider two other distributional aspects of interest: 1) the regional impacts of the tax swap; and 2) impacts across racial and ethnic groups. Table 8 presents regressions on the change in tax payment that include indicators for eight of the nine Census divisions (New England is the omitted division). Results are similar whether I include controls for household attributes or not. While there is some variation, it is modest. Every census division pays less in taxes under the reform than does New England. The Pacific region is closest in impact to New England; the West South Central division (Arkansas, Louisiana, Oklahoma, and Texas) have the largest decline ($8.44 per household on average) followed by the Mountain states (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming) at $6.76. Table 9 shows results from regressions with an indicator for the household being in a rural area. Households in rural areas pay $7 less in taxes on average than do households in urban areas. This reflects the fact that vehicles in rural areas tend to have lower fuel economy (20.0 miles per gallon) than vehicles in urban areas (22.3 miles per gallon). Vehicles in rural areas are driven more but only by 5.6 percent on average relative to vehicles in urban areas.

Over one-half of households see a tax increase with a VMT-gas tax swap. Rural households are 21 percentage points less likely than urban households to face a tax increase. And while 2 percent of households see a tax increase of $50 or more, rural households are .75 percentage points less likely to see such a large increase in taxes.

Differences across racial or ethnic lines are less pronounced. Households where the survey respondent is Black or African American pay between $.14 and $.38 less in taxes than other respondents

and we can't reject a zero difference at any reasonable level of statistical significance. Similarly households with a Hispanic survey respondent pay between $.30 and $1.00 less in taxes than other households (both sets of regressions available upon request).

VI. Conclusion

The increasing electrification of the transportation fleet calls into question the ability of the current motor vehicle fuel excise tax (gasoline and diesel) to raise sufficient funding for the Highway Trust Fund. One possible solution to the problem is to shift from a tax on fuel consumption to a vehicle miles traveled (VMT) tax. Advances in technology make this administratively practicable though there are concerns about privacy and the impact that such a tax might have on the consumer demand for fuel efficient vehicles as well as electric and plug-in hybrid vehicles. Another concern is whether the tax swap might exacerbate the current regressive nature of fuel taxes. This paper demonstrates that this latter problem should not be an issue. A VMT-gas tax swap is shown to be modestly progressive over much of the income distribution and that the progressivity is only going to grow as the vehicle fleet becomes more fuel efficient and increasingly electrified. Regional variation is also modest with drivers in rural communities likely to benefit from the tax swap.

With the rapidly increasing share of EVs and PHEVs in the marketplace, further analysis to explore how this higher share affects the distributional impact of a VMT-gas tax swap would be useful. The analysis here could be refined in a number of ways, including allowing for vehicle heterogeneity within households in EV take-up rates. Sensitivity analysis with different assumptions about EV market penetration as well as improvements in fleet fuel economy would also be valuable.

In the end, personal fuel consumption is quite modest for most drivers. So a VMT-gas tax swap entails a modest change in tax collections. But optics matter and the progressive nature of the tax swap should be heartening to proponents of this tax reform.

Table 1. 2017 NHTS Vehicles Sample

Initial Sample Size	256,115
Drop RVs, motorcycles, etc.	-12,209
Drop if more than 5 vehicles	-8,628
Drop if household income missing	-7,493
drop if annual VMT missing	-1,061
drop if annual VMT outliers (NHTS)	-16,455
drop upper and lower 0.5% tail of VMT	-2,101
Remaining Sample	208,168

Table 2. Vehicle Summary Statistics

All Vehicles: N=208,168				
	Mean	S.D.	Min	Max
Fuel Intensity	49.1	12.7	0.0	166.7
VMT	10,517	7,109	69	42,694
Fuel	507.5	370.2	0.0	5,210.3
Cars: N=104,889				
	Mean	S.D.	Min	Max
Fuel Intensity	42.0	8.9	0.0	90.9
VMT	10,261	7,086	69	42,694
Fuel	421.0	297.6	0.0	2,542.6
Vans: N=11,303				
	Mean	S.D.	Min	Max
Fuel Intensity	53.3	8.1	0.0	166.7
VMT	11,243	7,146	69	42,666
Fuel	594.9	405.9	0.0	5,210.3
SUVs: N=52,860				
	Mean	S.D.	Min	Max
Fuel Intensity	52.7	10.4	0.0	90.9
VMT	11,426	7,053	69	42,686
Fuel	594.3	383.1	0.0	3,518.4
Pickup Trucks: N=38,515				
	Mean	S.D.	Min	Max
Fuel Intensity	64.3	10.3	20.0	166.7
VMT	9,674	7,049	70	42,663
Fuel	617.9	462.9	4.1	4033.1

Table 3. Household Summary Statistics

Variable	Mean	Std. Dev	Min	Max
Household Income	81,189	70,376	5,000	300,000
Household Size	2.56	1.36	1	13
Number of Adults	1.95	0.80	1	8
Number of Drivers	1.85	0.78	0	7
Number of Workers	1.26	0.92	0	7
Homeowner	0.68	0.47	0	1
Children in Home	0.36	0.48	0	1
Urban Area	0.82	0.39	0	1
Urban Block	0.37	0.48	0	1
Rural Block	0.19	0.39	0	1
Population Density (per square mile)	49.7	64.8	0.5	300
Number of Vehicles	2.04	1.02	1	5
HH Average Fuel Intensity	47.87	10.23	0	166.67
HH Total Mileage	19,347	13,915	70	133,851
HH Total Fuel Consumption	933.6	724.8	0.0	7,495.8
Summary statistics over 113,434 households with vehicles in the NHTS. Average fuel intensity weighted by vehicle miles travelled.				

Table 4. Fuel Intensity Regressions

	(1)	(2)	(3)	(4)
Ln(HH Income)	-0.701 (0.035)**	-1.103 (0.038)**	-0.551 (0.034)**	-1.021 (0.037)**
Household Size		1.263 (0.055)**		1.208 (0.054)**
Number of Adults		-1.001 (0.092)**		-0.869 (0.091)**
Number of Drivers		-1.361 (0.089)**		-1.391 (0.088)**
Number of Workers		-0.660 (0.039)**		-0.642 (0.039)**
Homeowner		1.143 (0.079)**		1.165 (0.079)**
Children in Home		-0.854 (0.114)**		-0.855 (0.113)**
Urban Area		-1.166 (0.107)**		-1.377 (0.105)**
Urban Block		0.284 (0.080)**		-0.044 (0.081)
Rural Block		1.667 (0.107)**		1.802 (0.105)**
Population Density		-0.000 (0.000)**		-0.000 (0.000)**
Number of Vehicles		2.570 (0.037)**		2.483 (0.037)**
Intercept	57.180 (0.383)**	58.013 (0.405)**	55.508 (0.381)**	57.295 (0.405)**
R^2	0.00	0.07	0.02	0.08
N	208,167	207,961	208,167	207,961
State Fixed Effects?	No	No	Yes	Yes

Dependent Variable: gallons per 1000 miles. Standard errors clustered at the household level.

** - p value equal to 0.01 or less

Table 5. Change in Tax Payments Regressions

	(1)	(2)	(3)	(4)
Ln(HH Income)	0.527 (0.075)**	0.019 (0.075)	1.252 (0.085)**	0.938 (0.085)**
Household Size			-3.090 (0.108)**	-3.029 (0.107)**
Number of Adults			2.560 (0.176)**	2.202 (0.176)**
Number of Drivers			3.113 (0.177)**	3.252 (0.176)**
Number of Workers			1.619 (0.096)**	1.728 (0.096)**
Homeowner			-0.867 (0.159)**	-0.913 (0.159)**
Children in Home			1.916 (0.239)**	1.847 (0.237)**
Urban Area			3.849 (0.278)**	4.079 (0.277)**
Urban Block			-0.265 (0.177)	0.101 (0.178)
Rural Block			-4.322 (0.276)**	-3.852 (0.276)**
Population Density			0.011 (0.001)**	0.002 (0.001)
Number of Vehicles			-5.220 (0.091)**	-5.117 (0.091)**
Intercept	-5.711 (0.820)**	-0.158 (0.823)	-10.791 (0.917)**	-7.316 (0.926)**
R^2	0.00	0.03	0.08	0.09
N	112,774	112,774	112,663	112,663
State Fixed Effects?	No	Yes	No	Yes

Dependent Variable: change in tax payments.
** - p value equal to 0.01 or less

Table 6. Change in Tax Payments Regressions: Lifetime Income Analysis

	(1)	(2)	(3)	(4)
Ln(HH Income)	1.018 (0.141)**	0.367 (0.141)**	1.557 (0.163)**	1.089 (0.163)**
Household Size			-3.242 (0.213)**	-3.333 (0.212)**
Number of Adults			3.516 (0.307)**	3.178 (0.306)**
Number of Drivers			2.665 (0.304)**	2.809 (0.302)**
Number of Workers			1.563 (0.188)**	1.723 (0.186)**
Homeowner			0.454 (0.323)	0.460 (0.321)
Children in Home			1.931 (0.445)**	2.075 (0.441)**
Urban Area			4.665 (0.509)**	4.971 (0.505)**
Urban Block			-0.940 (0.338)**	-0.318 (0.340)
Rural Block			-6.073 (0.510)**	-5.437 (0.509)**
Population Density			0.014 (0.003)**	0.001 (0.003)
Number of Vehicles			-5.118 (0.158)**	-5.003 (0.157)**
Intercept	-12.715 (1.585)**	-5.444 (1.584)**	-17.496 (1.789)**	-12.156 (1.797)**
R^2	0.00	0.04	0.07	0.10
N	40,308	40,308	40,263	40,263
State Fixed Effects?	No	Yes	No	Yes

Dependent Variable: change in tax payments. Households limited to those with head of household between the ages of 40 and 60.
** - p value equal to 0.01 or less

Table 7. Change in Tax Payments Regressions:
Simulation with Higher Fuel Economy and EV/PHEV Market Penetration

	(1)	(2)	(3)	(4)
Ln(HH Income)	15.178 (0.113)**	14.327 (0.114)**	16.520 (0.127)**	16.144 (0.128)**
Household Size			-1.004 (0.162)**	-1.043 (0.162)**
Number of Adults			1.857 (0.265)**	1.503 (0.265)**
Number of Drivers			-2.629 (0.266)**	-2.464 (0.265)**
Number of Workers			-0.873 (0.144)**	-0.738 (0.144)**
Homeowner			4.597 (0.239)**	4.649 (0.239)**
Children in Home			5.593 (0.358)**	5.654 (0.358)**
Urban Area			7.781 (0.417)**	7.897 (0.417)**
Urban Block			3.090 (0.266)**	3.524 (0.269)**
Rural Block			-7.984 (0.415)**	-7.499 (0.416)**
Population Density			0.048 (0.002)**	0.036 (0.002)**
Number of Vehicles			-5.038 (0.137)**	-4.948 (0.137)**
Intercept	-166.007 (1.245)**	-156.681 (1.251)**	-179.048 (1.377)**	-174.647 (1.395)**
R^2	0.14	0.16	0.22	0.23
N	112,774	112,774	112,663	112,663
State Fixed Effects?	No	Yes	No	Yes

Dependent Variable: change in tax payments.
** - p value equal to 0.01 or less

Table 8. Regional Variation in Tax Payments

	(1)	(2)
Middle Atlantic	-2.628	-2.767
	(0.370)**	(0.360)**
East North Central	-5.188	-4.145
	(0.356)**	(0.346)**
West North Central	-8.323	-6.589
	(0.402)**	(0.392)**
South Atlantic	-3.799	-3.039
	(0.346)**	(0.337)**
East South Central	-7.301	-5.547
	(0.413)**	(0.403)**
West South Central	-9.450	-8.438
	(0.367)**	(0.358)**
Mountain	-8.266	-6.763
	(0.398)**	(0.388)**
Pacific	-1.554	-0.865
	(0.356)**	(0.347)*
Other Covariates	No	Yes
R^2	0.02	0.07
N	112,774	112,757

Dependent Variable: change in tax payments. Regional coefficient estimates are all relative to New England. Other covariates are those included in Table 7.

* - p value equal to 0.05 or less

** - p value equal to 0.01 or less

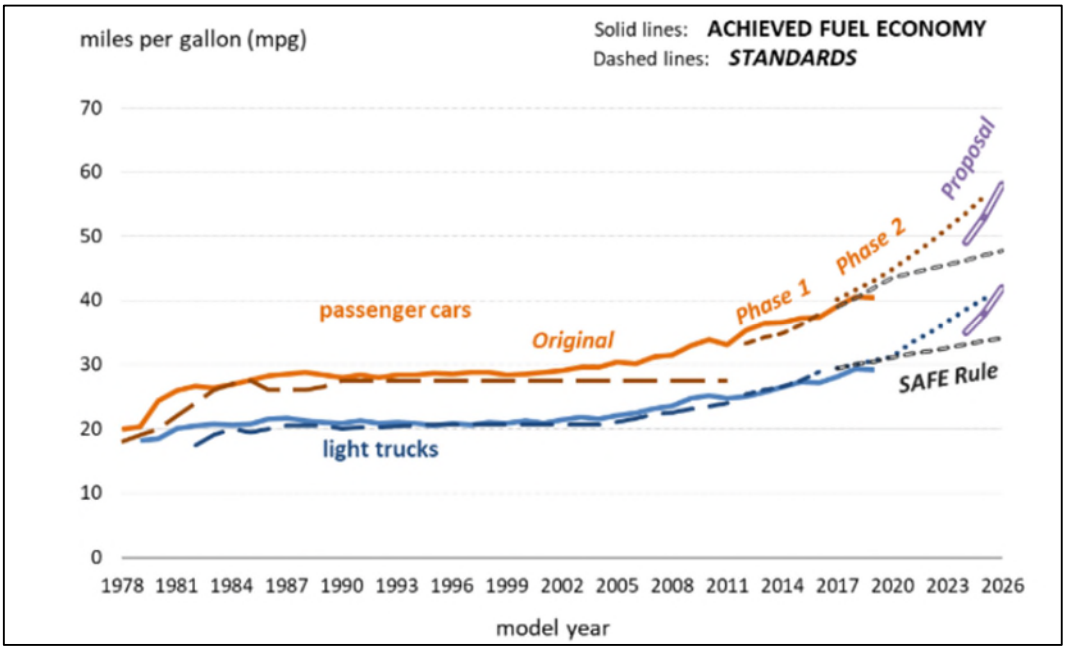
Table 9. Rural/Urban Variation in Tax Payments

	(1)	(2)	(3)	(4)
Rural Indicator	-10.380 (0.174)**	-9.630 (0.180)**	-7.556 (0.177)**	-7.045 (0.182)**
Other Covariates	No	No	Yes	Yes
State Fixed Effects	No	Yes	No	Yes
R^2	0.03	0.05	0.07	0.09
N	112,774	112,774	112,757	112,757

Dependent Variable: change in tax payments. Other covariates are those included in Table 7.

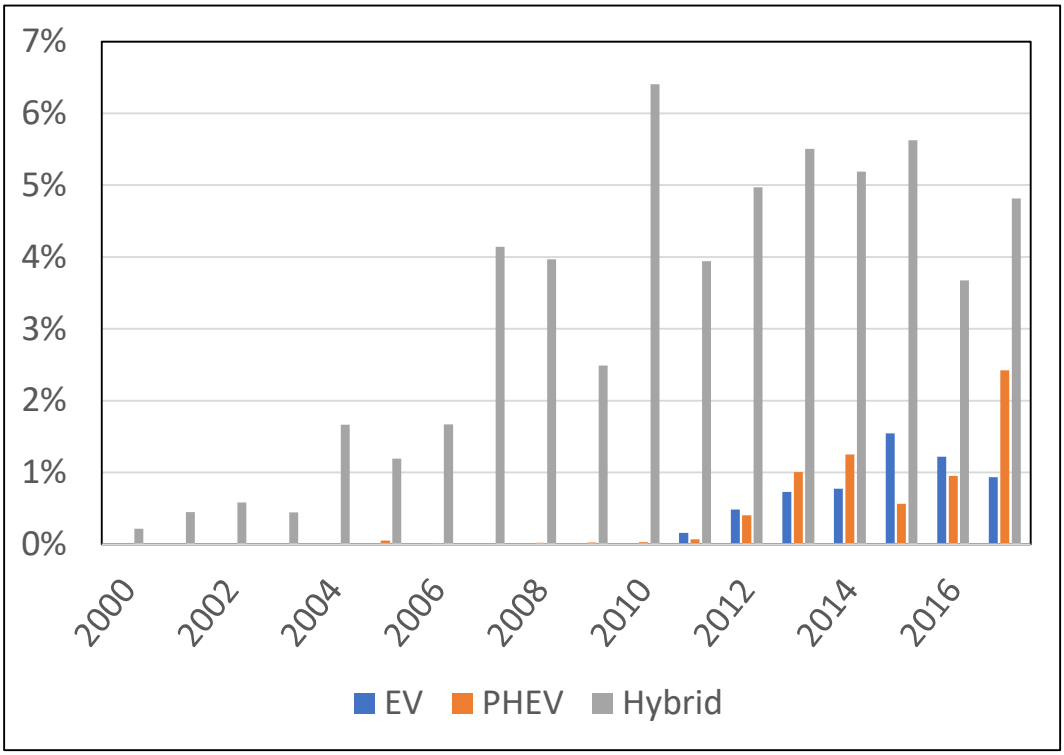
** - p value equal to 0.01 or less

Figure 1. Fuel Economy Standards



Source: Congressional Research Service (2021)

Figure 2. Market Penetration of Hybrid Vehicles by Model Year



Source: Author's Calculation from 2017 NHTS Data

Figure 3. Relation of the Change in the Average Tax Rate
and the Income Elasticity of Fuel Intensity

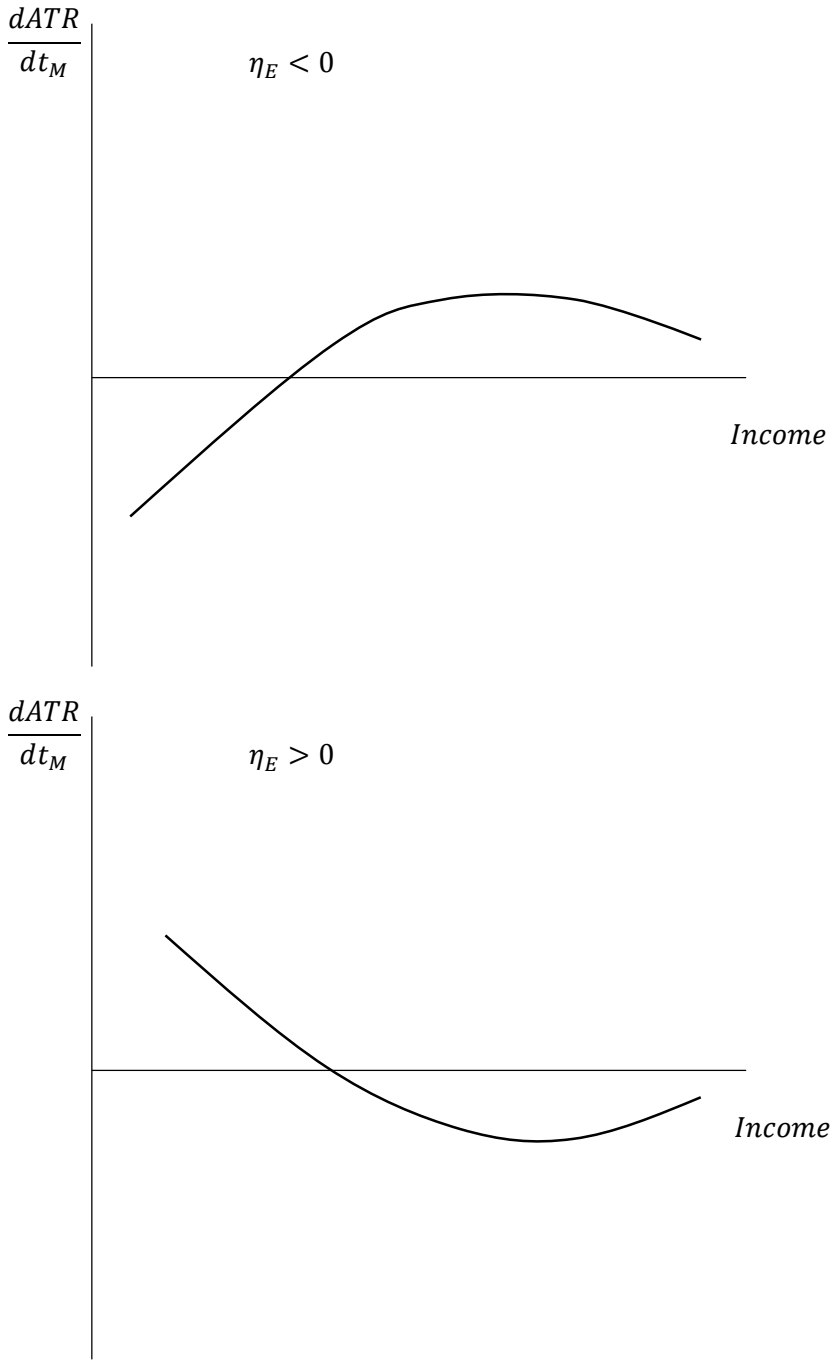


Figure 4. Impact of Household Income on Fuel Intensity



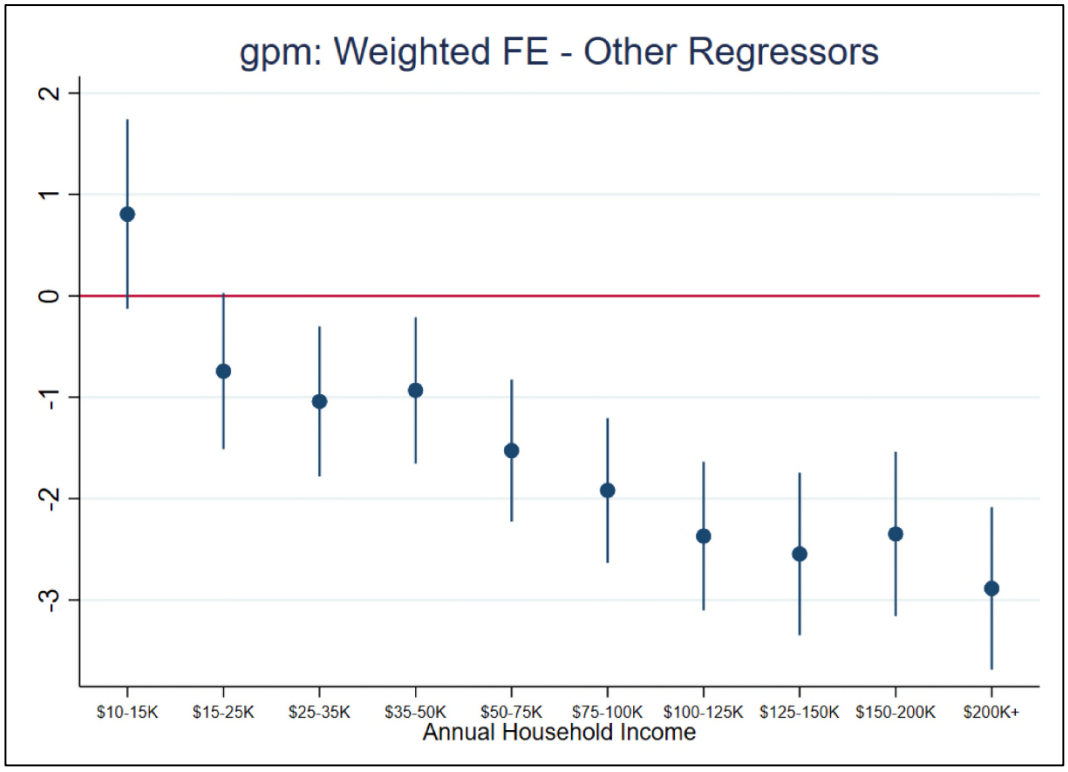


Figure 5. Impact of Household Income on Change in Tax Payments

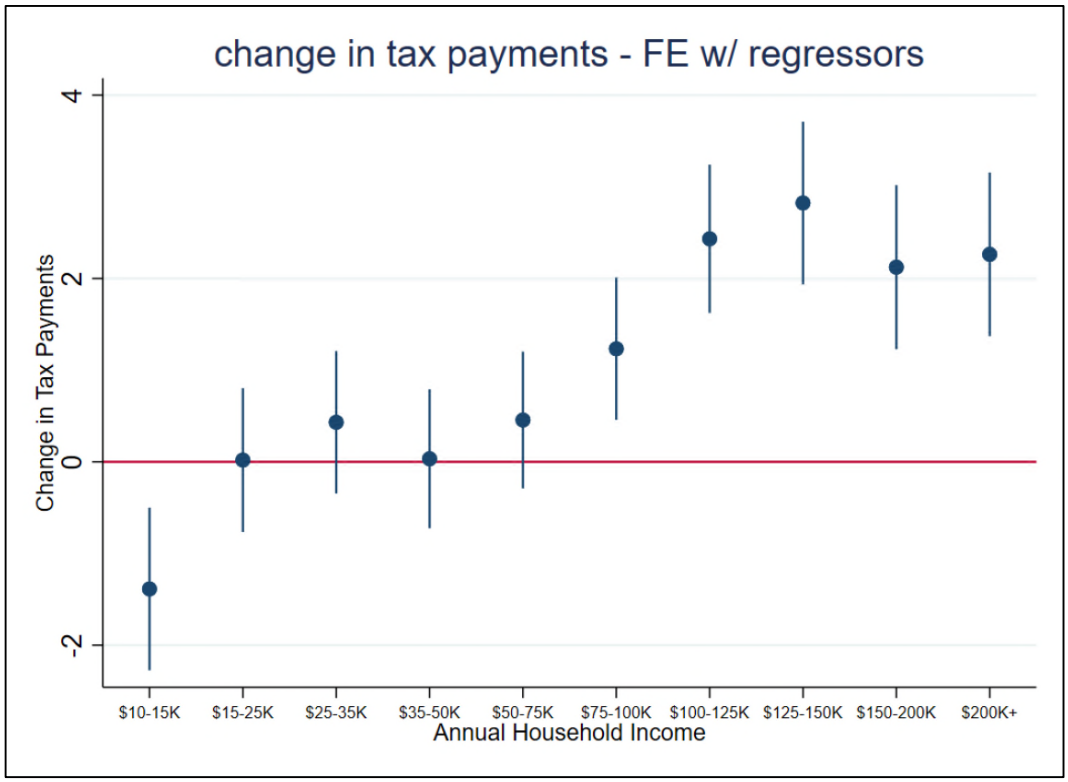
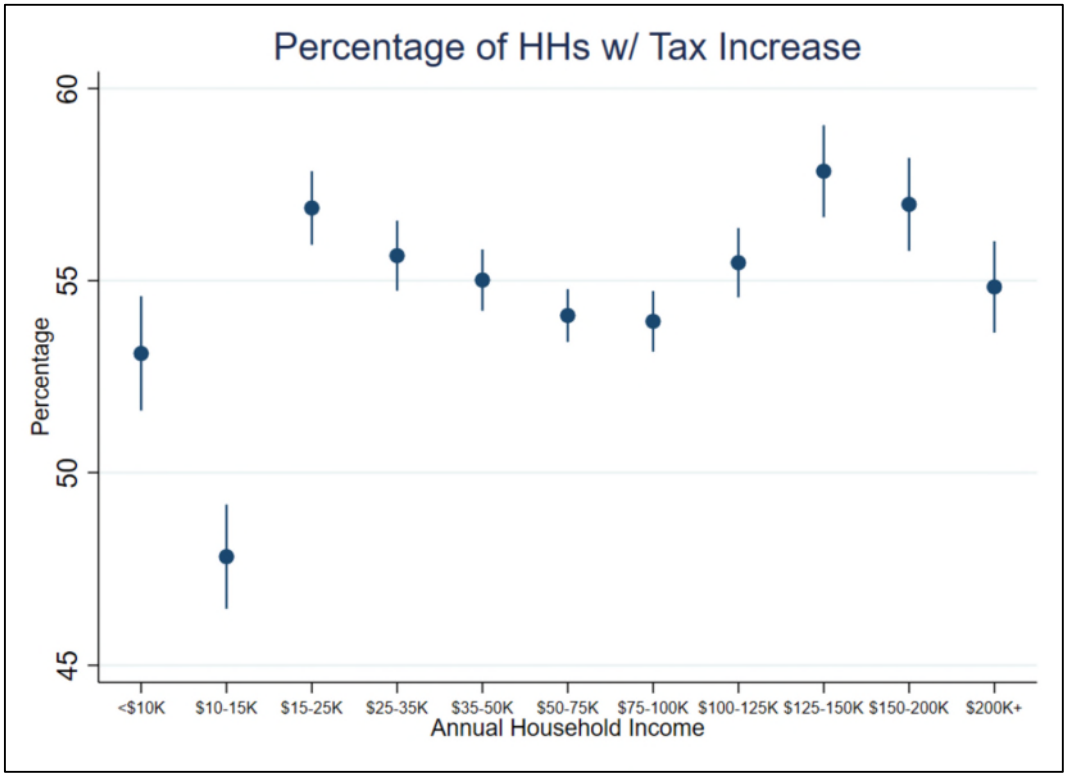


Figure 6. Heterogeneity in Tax Payment Change



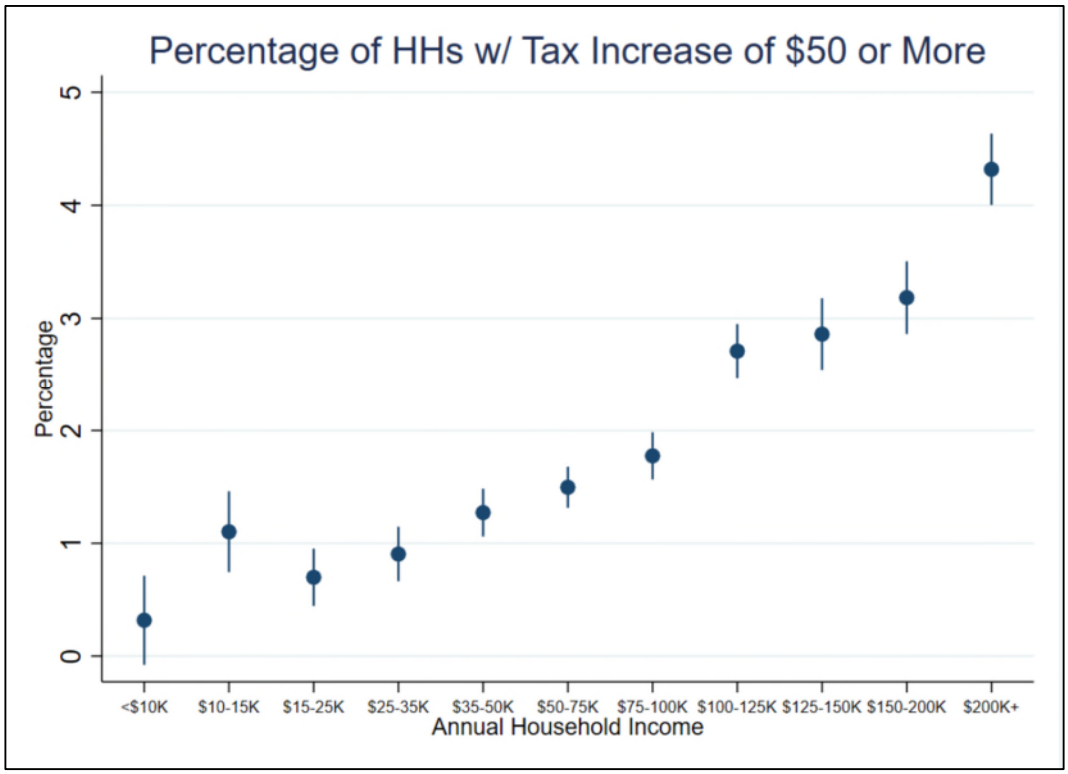
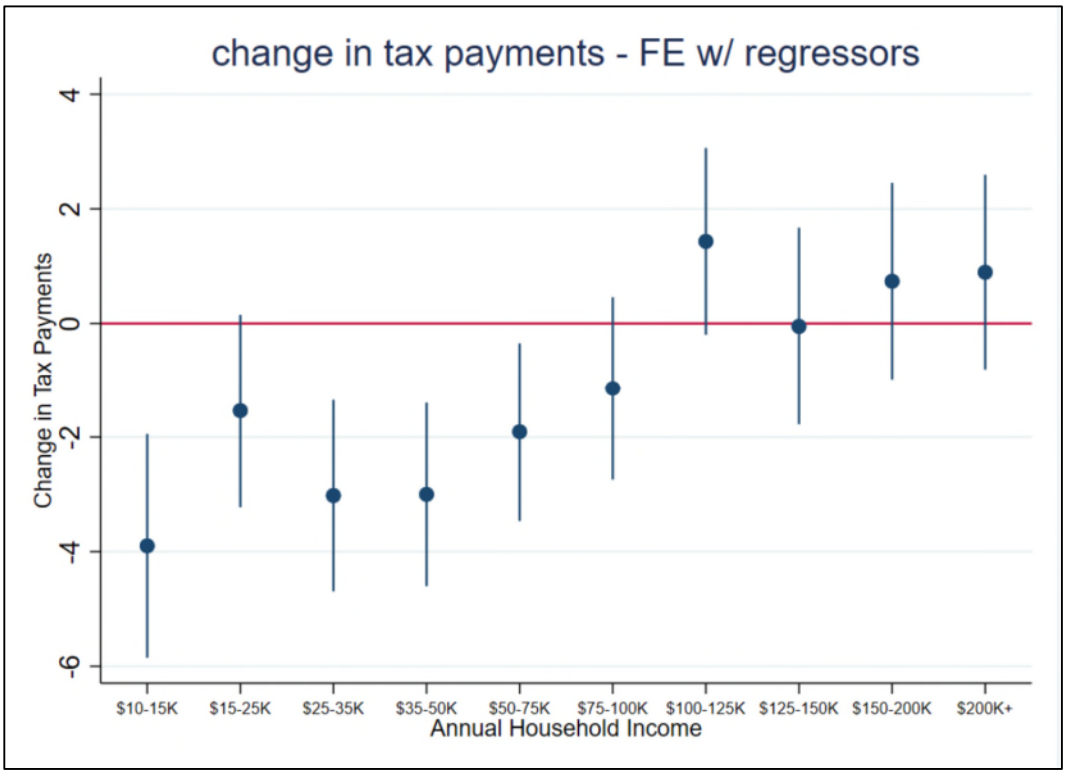


Figure 7. Change in Tax Payments: Lifetime Income Analysis



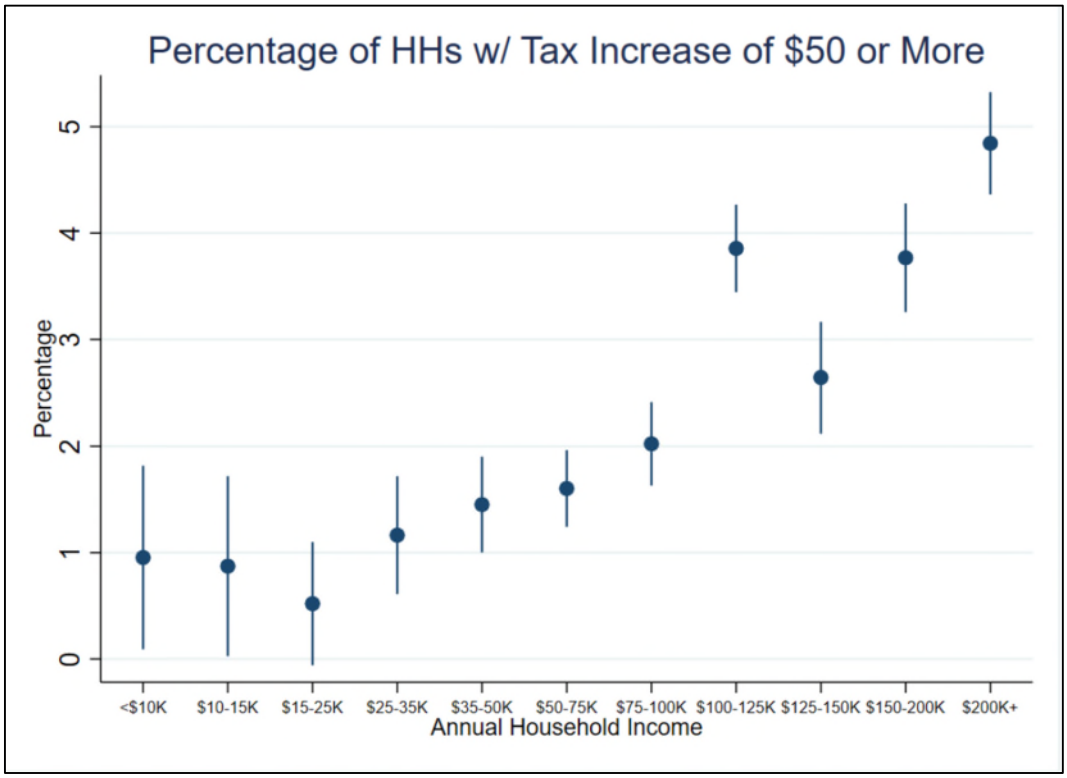
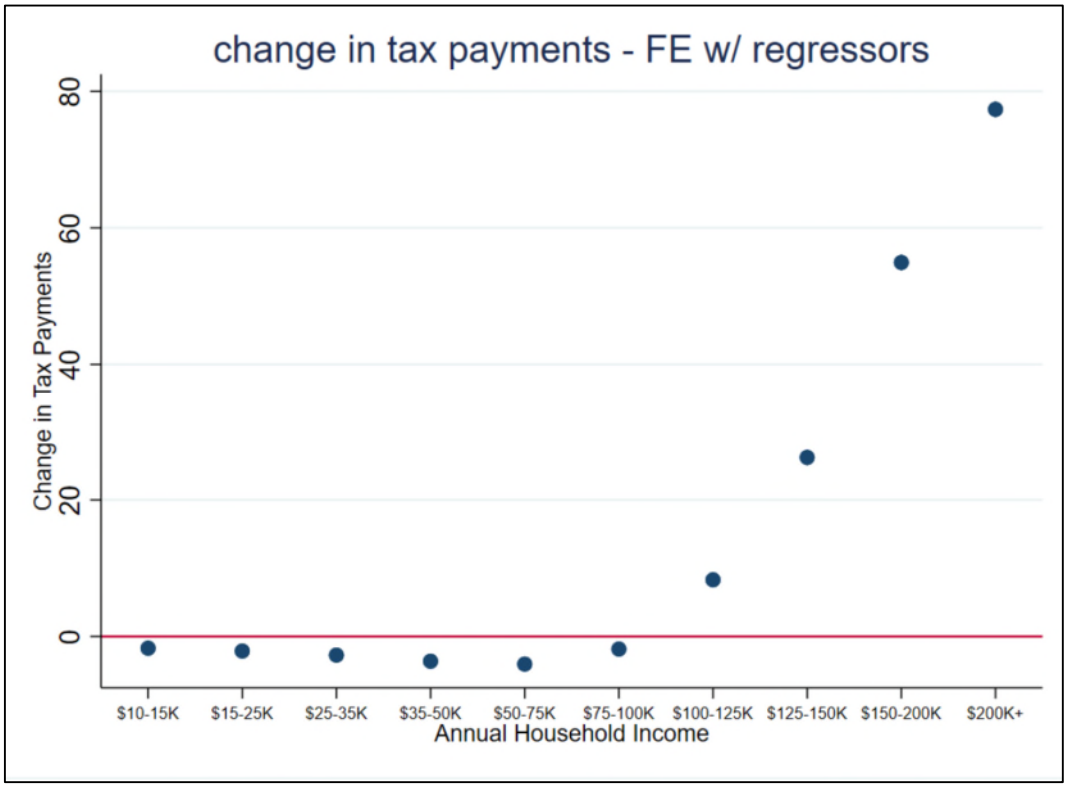
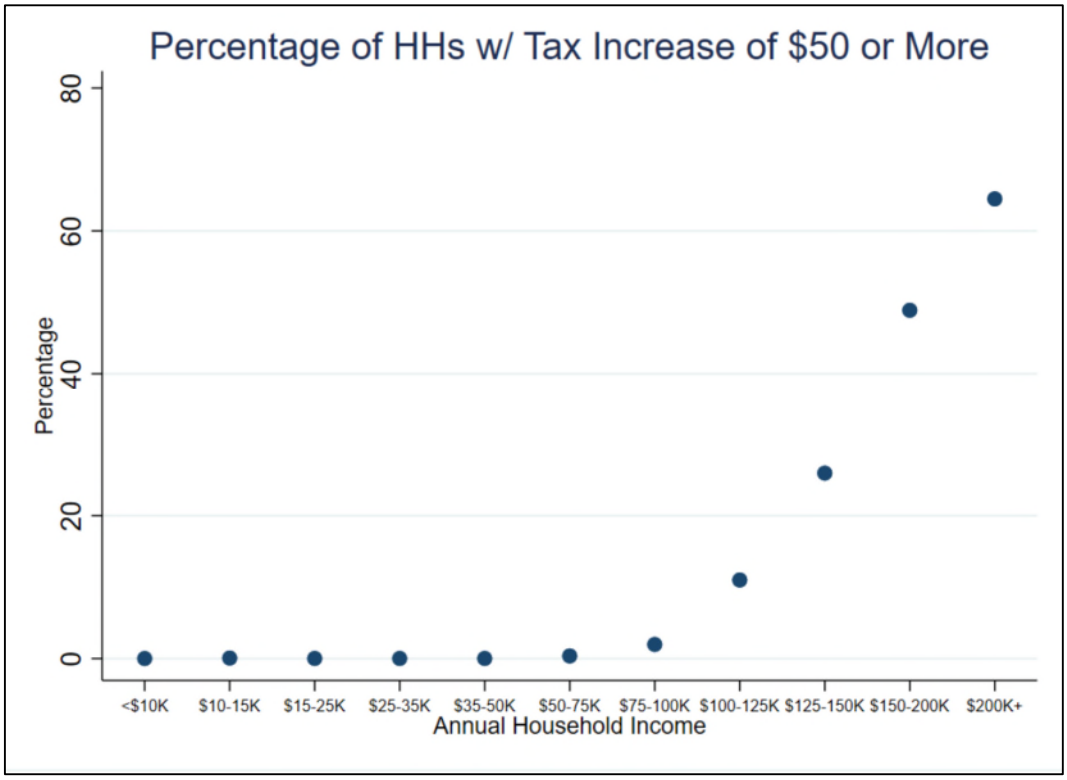


Figure 8. Change in Tax Payments:
Simulation with Higher Fuel Economy and Market Penetration of EVs and PHEVs





Appendix

1. Measuring the Welfare Change

The VMT tax shift policy changes the price of driving per mile (p_M) and the price of fuel (p_F). The change in welfare (as measured by equivalent variation) for this policy is

$$\Delta W \equiv EV = e(p_M^0, p_F^0, u^1) - e(p_M^1, p_F^1, u^1)$$

where $e(\cdot)$ is the expenditure function at given prices and utility and the superscript 0 indicates pre-policy prices and superscript 1 indicates post-policy prices and utility. Ignoring non-driving related spending, the expenditure function is

$$e(p_M, p_F, u) = p_M M(p_M, u) + p_E E(p_F, u)$$

where *M* and *E* are compensated demands and p_E is the price of fuel intensity (the reciprocal of the price of fuel economy). Since $p_M = p_F E + t_M$, and $F = E \cdot M$,

$$e(p_M, p_F, u) = p_F F(p_M, u) + t_M M(p_M, u) + p_E E(p_F, u).$$

Rewrite this expression as

$$\Delta W = e(p_M^0, p_F^0, u^1) - e(p_M^1, p_F^0, u^1) + e(p_M^1, p_F^0, u^1) - e(p_M^1, p_F^1, u^1).$$

By the Envelope theorem,

$$\frac{\partial e(p_M, p_F, u)}{\partial t_M} = M(p_M, u)$$

and

$$\frac{\partial e(p_M, p_F, u)}{\partial p_F} = F(p_F, t_M, u).$$

Therefore

$$\Delta W = \int_{t_M^1}^{t_M^0} M^c(p_M, p_F^0, u^1) dp_M + \int_{p_F^1}^{p_F^0} F^c(t_M^1, p_F, u^1) dp_F.$$

We can approximate the areas under these compensated demand curves with areas under the Marshallian demands. Again, this approximation should be reasonable so long as income effects are not too large (Willig, 1976).

$$\Delta W \cong \int_{t_M^1}^{t_M^0} M(p_M, p_F^0, Y)dp_M + \int_{p_F^1}^{p_F^0} F(t_M^1, p_F, Y)dp_F.$$

Taking a linear approximation to this yields the further approximation

$$\Delta W_i = -\left(\frac{M_{0i} + M_{1i}}{2}\right)dt_M - \left(\frac{F_{0i} + F_{1i}}{2}\right)dp_F.$$

Assuming small impacts on driving and fuel consumption[24], this becomes

$$\Delta W_i = -M_i t_M - F_i dp_F.$$

2. Estimates of Demand Changes for VMT and Fuel Efficiency from Tax Swap

The change in demand for VMT is equal to

$$dM_i = \frac{\partial M_i}{\partial p_M}dp_M = \frac{\partial M_i}{\partial p_M}\{E_i dp_F + dt_M\}$$

and the change in demand for fuel efficiency equals

$$dE_i = \frac{\partial E_i}{\partial p_F}dp_F.$$

Using elasticities from Small and van Dender (2007), we can calculate the change in short or long-run demand for VMT and fuel intensity:

$$dlnM_i = \varepsilon_{M,p_M} dlnp_M = \varepsilon_{M,p_M}\left(\frac{E_i dp_F + dt_M}{E_{0i} p_{0F}}\right)$$

and

$$dlnE_i = \varepsilon_{E,p_F} dlnp_F.$$

[24] The median percentage price change in the dataset for a 10 cent drop in the fuel excise tax rate is 4%. Given a long run price elasticity demand for fuel efficiency of .20, E falls by less than 1 percent. Similarly, the median percentage price change per mile is -.04. Given a long run price elasticity demand for VMT of -.22, miles driven rises by less than 1 percent and fuel consumption is essentially unchanged. See Appendix 2 for details.

Table A1 presents elasticity estimates from Small and Van Dender (2007b).

Table A1. Vehicle Price Elasticities		
	Short Run	Long Run
ε_{M,p_M}	-0.0452	-.2221
ε_{E,p_F}	-0.0440	-0.2047
Source: Small and Van Dender (2007), Table 5		

From a static (no behavioral change) model, the VMT tax rate that offsets a 10 cent per gallon decrease in the motor fuel excise tax is 0.486 cents per mile. Assuming average fuel intensity in the 2017 NHTS data set along with the average price of gasoline, the long run changes in fuel intensity and VMT is less than one percent.

3. Reduced Form Income Elasticity of Demand for VMT

Small and Van Dender (2007b) estimate a three equation system of VMT, vehicle ownership, and fuel efficiency (inverse). They find a SR income elasticity of VMT (η_M) of 0.11 and a LR estimate of 0.53. This is conditional on efficiency and number of vehicles owned. Following their rebound approach, I can combine the M and V equations to get a reduced form VMT equation that incorporates the number of vehicles chosen. The reduced form SR income elasticity is

$$\eta_{\widehat{M}} = \frac{\varepsilon_{M,V}\eta_V + \eta_M}{1 - \varepsilon_{M,V}\varepsilon_{V,M}} = 0.1125.$$

To get the LR elasticity, I need to divide each elasticity by one minus the lagged dependent variable coefficient for the relevant regression. The LR elasticity estimate is 0.5849.

4. Rebound

For the simulation where we assume a major increase in fuel economy, it is likely that the lower price of driving per mile (due to higher fuel efficiency) will lead to more driving. This is the rebound effect. I incorporate this rebound effect by increasing vehicle miles traveled for all cars. I assume a 10 percent rebound effect based on a recent review of the literature by Gillingham (2018).

Let ϕ represent the percentage increase in fuel economy. Let 0 indicate the period before an increase in fuel economy and 1 the period after the increase. Absent a rebound effect, gasoline consumption (F) after the increase in fuel economy would be

$$\hat{F}_1 = \frac{M_0}{\psi_1} = \frac{M_0}{\psi_0(1+\phi)} = \frac{F_0}{1+\phi},$$

where the hat indicates the counterfactual fuel consumption without rebound, M is vehicle miles traveled, and ψ is fuel economy (miles per gallon). The projected fuel saving (absent rebound) is

$$F_0 - \hat{F}_1 = F_0\left(1 - \frac{1}{1+\phi}\right) = F_0\left(\frac{\phi}{1+\phi}\right).$$

With a rebound effect of ρ, the actual fuel savings will be

$$F_0 - F_1 = (1-\rho)\left(F_0 - \hat{F}_1\right) = (1-\rho)F_0\left(\frac{\phi}{1+\phi}\right),$$

and actual fuel consumption is

$$F_1 = F_0\left(1 - (1-\rho)\left(\frac{\phi}{1+\phi}\right)\right).$$

Actual driving is

$$M_1 = \psi_1 F_1 = \psi_1 F_0\left(1 - (1-\rho)\left(\frac{\phi}{1+\phi}\right)\right) = (1+\phi)\psi_0 F_0\left(1 - (1-\rho)\left(\frac{\phi}{1+\phi}\right)\right)$$

$$= M_0(1 + \phi - (1-\rho)\phi) = M_0(1+\rho\phi).$$

Assuming a rebound factor of 10 percent and a 40 percent increase in fuel economy, driving would increase by 4 percent.

5. Logit Regressions for EV and PHEV Ownership

	EV	PHEV
Ln(HH Income)	1.326 (0.081)**	1.171 (0.078)**
Household Size	0.005 (0.086)	0.011 (0.093)
Number of Adults	0.035 (0.155)	0.066 (0.163)
Number of Drivers	-0.281 (0.148)	-0.239 (0.157)
Number of Workers	-0.036 (0.069)	-0.011 (0.070)
Homeowner	0.373 (0.182)*	0.294 (0.170)
Children in Home	0.350 (0.178)*	0.161 (0.191)
Urban Area	0.268 (0.230)	0.217 (0.230)
Urban Block	-0.060 (0.127)	0.373 (0.126)**
Rural Block	-0.798 (0.256)**	-0.270 (0.238)
Population Density	0.005 (0.001)**	0.002 (0.001)*
Number of Vehicles	0.078 (0.059)	-0.152 (0.065)*
Intercept	-21.915 (0.956)**	-19.655 (0.917)**
N	207,424	207,424

Dependent Variable: EV or PHEV vehicle.
Standard errors clustered at the household level.
* - p value equal to 0.05 or less
** - p value equal to 0.01 or less

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