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From Tank to Odometer:
Winners and Losers from a Gas-to-VMT Tax Shift

Christopher R. Knittel, Gilbert E. Metcalf, and Shereein Saraf*

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Abstract

With the increase in fuel economy of the personal transportation fleet along with the increased penetration of hybrid and electric vehicles, federal motor vehicle fuel excise tax revenue has been steadily declining. This has led to calls for finding a replacement for this tax. One option is to replace the gas tax with a vehicle miles traveled (VMT) tax. To investigate the impact of such a tax swap, we combine data from the 2017 National Household Transportation Survey (NHTS) and the American Community Survey (ACS). Using machine learning techniques, we generate estimates of VMT and gasoline tax collections at the census tract level. This allows us to explore the distributional implications of this tax swap at a geographically disaggregated level. We find, as have previous researchers, that this tax swap is modestly progressive. Our more granular geographic analysis highlights striking disparities not previously reported. We find that rural areas and census tracts in the center of the country generally benefit from this tax swap, while urban and bicoastal areas generally experience higher taxation. Additionally, Republican-leaning districts, which overlap significantly with rural areas, see marked gains compared to Democratic districts. The results highlight the potential for a VMT tax to address longstanding inequities in transportation funding while offering a politically salient narrative.

JEL Classification Codes: H22, H23, Q48, R48

Keywords: Energy, Taxation, Transportation, Incidence

Knittel: George P. Shultz Professor Sloan School of Management, Director MIT Center for Energy and Environmental Policy Research, Director MIT Climate Policy Center, and NBER, knittel@mit.edu. *Metcalf:* John DiBiaggio Professor of Citizenship and Public Service Emeritus, Tufts University, Visiting Professor, Sloan School of Management, and NBER, metcalfg@mit.edu. *Saraf:* Center for Energy and Environmental Policy Research, MIT, ssaraf@mit.edu.

1 Introduction

The design of transportation taxation has long been a critical issue in public finance, with policymakers seeking systems that are both efficient and equitable. In the United States, the federal gas tax—a longstanding mechanism for funding transportation infrastructure—has faced increasing scrutiny due to its declining revenues and concerns about fairness. This decline is largely driven by improvements in fuel efficiency and the accelerating adoption of electric vehicles (EVs), which do not contribute to gas tax revenues. As EV adoption grows, particularly in urban areas and coastal states, federal gas tax revenues are falling and are projected to continue falling (see Figure 1 with actual gas tax revenue through 2023 and projections to 2031). By law, revenues from this tax are earmarked for the Federal Highway Trust Fund, which finances a major portion of state and federal roadwork in the United States. This has led policymakers and analysts to explore options for replacing the gas tax. One option gaining traction is a vehicle miles traveled (VMT) tax, which charges drivers based on the distance they travel rather than the fuel they consume. This paper examines the winners and losers from transitioning the federal gas tax to a revenue-equivalent VMT tax, focusing on the distributional impacts across geography and political affiliation.

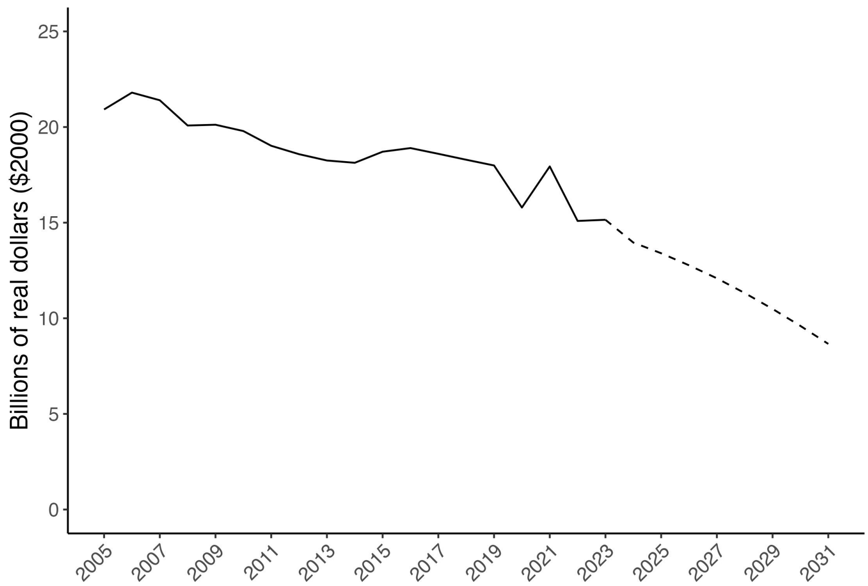
Previous research has explored the income-based distributional effects of transportation taxes. This paper confirms the findings of these studies, showing that the shift from a gas tax to a VMT tax is progressive, benefiting lower-income households. However, we expand on this literature by analyzing the impacts of the transition across geographic regions and political constituencies, areas that have been less explored in prior research, building on the methods in Green et al. (2025).

Our results show that while the shift is modestly progressive in terms of income, striking disparities emerge across geography. Rural areas and the center of the United States, which tend to experience lower average fuel efficiency, experience substantial benefits from a revenue-neutral VMT-Gas Tax swap. This effect is closely tied to the uneven geographic distribution of EV adoption: urban areas and coastal regions, where EV penetration is highest, are less reliant on the gas tax and benefit less from a shift to VMT-based taxation.

Additionally, Republican-leaning districts, which overlap significantly with rural areas, see marked advantages compared to Democratic districts. The results highlight the potential for a VMT tax to address longstanding inequities in transportation funding while offering a politically salient narrative. By documenting the geographic and political implications of this policy shift, this study contributes to the broader debate on how to design equitable and effective transportation taxation systems in a rapidly evolving mobility landscape.

The remainder of the paper is organized as follows. The next section highlights previous research that is relevant to our work. Section 3 describes our data and methods. Results follow in section 4. We conclude in section 5 with comments about policy implications and thoughts about future research.

Figure 1: Federal Gas Tax Revenue



Note: Revenue in billion dollars from the year 1999 to 2031. Actual revenue data through the year 2023. The dotted line shows projected data. Source: Actual gas tax revenue data until the year 2023 are from the IRS Statistics of Income Excise Tax Statistics. (Internal Revenue Service, 2023) Projected gas tax revenue data from the Congressional Budget Office Revenue Projections. (Congressional Budget Office, 2023a)

2 Previous Research

The literature on the distributional implications of a VMT-Gas tax swap is sparse. McMullen et al. (2010) used the 2001 National Household Travel Survey to simulate a tax swap for Oregon drivers and found the swap to be regressive. More recent research accounts for the growing penetration of plug-in hybrid and electric vehicles in the U.S. auto market. Using 2017 data, Metcalf (2023) analyzes the income incidence of replacing the gas tax with a carbon tax or VMT tax, finding evidence of progressivity under certain designs. Similarly, Glaeser et al. (2023) examine how mobility-related user fees, including the gas tax, affect households across the income distribution, highlighting the regressive nature of the gas tax and the potential for alternative systems to address this inequity.

The efficiency case for a VMT-Gas tax swap is less clear-cut. Parry and Small (2005) estimate that seventy percent of the externalities from driving are due to congestion and externalities. On this basis, taxing EVs would be efficient despite their zero tailpipe pollution. Congestion and accidents, however, vary both spatially and temporally, suggesting that a uniform VMT tax would not necessarily match damages with the tax rate efficiently. The pollution impacts of the electricity used to power EVs also vary (Holland et al., 2019). One externality often cited for EVs is the road wear due to the heavier weight of EV batteries. Road damage rises with axle weight by a power of four (Low et al., 2023). The Low et al. (2023) analysis notes, however, that any additional damage from heavier personal vehicles that are EVs relative to their gasoline-powered alternatives is trivial in comparison to the road wear from buses and heavy-goods-laden trucks, whether they are powered by diesel, hydrogen, or electricity. One could argue that shifting to a VMT tax ignores the pollution impacts of gasoline-powered vehicles. Moreover, there are likely positive externalities from EV adoption to the extent that learning by doing drives down the cost of EV production as this nascent technology matures. The first-best response would be to combine a carbon price on fossil fuels with a subsidy for the purchase of an EV, with the subsidy tied to the positive adoption externalities. We set aside the question of optimal tax and subsidy design for personal transportation to focus narrowly on the revenue erosion in the gas tax from the adoption of more efficient internal combustion vehicles and EVs.

Both the Metcalf (2023) and Glaeser et al. (2023) papers focus on the distributional impact across income groups. Metcalf (2023) provides a model that demonstrates the importance of the income elasticity of fuel intensity (gallons of gasoline per mile driven) with a VMT-gas tax swap being progressive (regressive) over much of the income range if this elasticity is negative (positive). The sign of this elasticity is an empirical matter. To the extent that higher-income households value fuel economy, whether in gasoline-powered vehicles or through a taste for electric vehicles, this elasticity will be negative. Conversely, if higher-income households prefer larger, more powerful gasoline-powered vehicles, the elasticity will be positive. Metcalf estimates that the income elasticity of fuel intensity is negative, albeit small. This suggests the tax swap should be modestly progressive. The data bear out that theoretical prediction.

Turning to a geographic distributional analysis, the Glaeser et al. (2023) paper is silent on this question. The Metcalf (2023) paper provides one table looking at regional variation across nine broad regions. He finds a higher burden of the tax on households in New England, Middle Atlantic, and Pacific states relative to other states. None of the other papers cited in either of these analyses does a geographic-based distributional analysis of a VMT-gas tax swap. This paper builds on that literature by focusing sharply on the geographic incidence of the VMT-gas tax swap.

3 Data and Methods

3.1 Representative Data

For the highly disaggregated geographic analysis we undertake, we need to generate a prediction of household travel at the census tract level. There are about 80,000 census tracts in the United States with an average of 4,000 households per tract. Unfortunately, a measure of vehicle miles traveled at the census tract level does not exist. Instead, we predict household level annual vehicle miles at the census tract level using data from the 2017 National Household Transportation Survey (NHTS 2017), a nationally representative household travel survey, that provides household-level data on annual vehicle miles traveled and other household demographic characteristics, such as income, age, race, education, and employment for about 7000 households (Federal Highway Administration, 2017). The survey also includes information on the number of vehicles owned by the household, type of vehicles, and the use of public transport to travel to work.[1]

The NHTS only provides geographic information at the nine Census division levels. Using household-level variables common to the NHTS and to the American Community Survey (ACS 2022), we construct a best-fit model from the NHTS and use that model to predict average household vehicle miles traveled at the tract level in the 2022 ACS. (U.S. Census Bureau, 2022)

Given the large number of possible variables available to us to predict household-level vehicle miles traveled, we use machine learning techniques to identify a best-fit model to apply to the ACS data. We describe our methodology next.

3.2 Machine Learning Model

Our methodology relies on the machine learning model used by Green et al. (2025). Specifically, we use an adaptive lasso model, which involves the two-step lasso developed by Zou (2006). Lasso models modify the least squares optimization target in ordinary least squares (OLS) regressions by including a penalty term, λ, that encourages shrinking the estimated coefficients toward zero and setting some estimated coefficients to zero. In effect, the penalty term trades off some mean square error for more parsimonious models. The two-step adaptive lasso approach begins by running a standard lasso model on a portion of the data (the "training" data). It then uses those coefficient estimates to form weights in a second-step lasso model

[1] We have also conducted the analysis using the 2022 NHTS. There are an order of magnitude fewer observations in that dataset. We also find anomalous results that are likely due to the impact of COVID on household travel patterns. In our regression, for example, we find that income is negatively associated with vehicle miles traveled. This is likely due to the greater flexibility of jobs held by higher-income households for remote work. We do find similar distributional results when using that dataset, albeit with significantly less precision.

cross-validation exercise.[2] Equation 1 shows this two-step adaptive lasso model.

$$L(y,\lambda) = \arg\min_{\beta} \left\| y - \sum_{j=1}^{p} x_j \beta_j \right\|^2 + \lambda \sum_{j=1}^{p} w_j \left| \beta_j \right| \tag{1}$$

where, $w_j = \frac{1}{|\hat{\beta}_j^1|}$, are the weights added to cross-validation second-step lasso regression. $\hat{\beta}_j^1$ is the j^{th} coefficient from the first-step lasso regression. As noted above, λ is the penalty term. A larger value of λ will force a more restrictive model selection (i.e., fewer variables used to predict household vehicle miles traveled). The lasso cross-validation can include one of the two choices of λ, i.e., λ_{min} and λ_{1se}. While λ_{min} minimizes the mean cross-validation error, λ_{1se} corresponds to the value λ such that the cross-validation error is within one standard error of the minimum λ.[3] This two-step approach allows us to overcome the problem of over-fitting arising from highly correlated independent variables.

We vary several features to determine the best-fit model. Our choices include two functional forms for the dependent variable (levels and logs), two penalty terms (λ_{min} and λ_{1se}), and two final prediction approaches for household vehicle miles traveled. We can predict VMT using the coefficients from the second-step lasso estimation (so-called lasso approach) or we can run an ordinary least squares regression on the variables identified in the second-step adaptive lasso procedure (so-called OLS approach). We also consider higher orders of our independent variables. The four possible independent variable matrices are as follows: (a) a base model with all variables in linear form, (b) a model with linear variables and squares of selected variables, (c) a model with linear variables and interactions between selected variables, and (d) a model with linear variables with both squares and interactions of selected variables.[4] This yields a set of 32 possible model fits in all.[5]

Out of the 32 models we run, we select the model with the highest out-of-sample test R-squared (which has the smallest out-of-sample test mean squared error) to predict the household annual vehicle miles traveled at the census tract level. Appendix Table A1 reports the out-of-sample test and train R-squared values for all possible model fits. It also reports the out-of-sample adjusted test R-squared. If more than one model has the same value for the out-of-sample R-squared statistic, we break ties by choosing the model with the higher out-of-sample adjusted R-squared. In the case of a tie at this second level, we choose the more conservative model, i.e, the model with fewer independent variables. Appendix Table A reports model fit statistics for the 32 models we run. Based on our selection criteria, the "best" fit model to predict household annual vehicle miles traveled includes the dependent variable in levels, regressors in linear form only (base), λ_{min}

[2] Refer to Green et al. (2025) for a detailed methodology.

[3] The parameter λ_{1se} is considered to give a more regularized (or restrictive) variable selection and is the default option in most machine learning models.

[4] Squares of all continuous variables are added to the models including square terms. We have two such variables in our dataset—log of income and miles per gallon.

[5] Two λs $\times$ two dependent variables $\times$ two predict functions $\times$ four independent variable matrices.

as the cross-validation λ, and the lasso approach to predicting VMT.

Appendix Table A2 provides the summary statistics for vehicle miles traveled. The first row presents statistics from the 2017 NHTS "test" dataset, a subset of 33,683 observations from that dataset from which the model is estimated.[6] The second row reports statistics on predicted annual household VMT from the two-step adaptive Lasso procedure, where we use the estimated coefficients from that model (our preferred model). The third row presents summary statistics where we run OLS on the variables identified in the two-step Lasso procedure. While not our preferred model, we include it to show that our estimated VMT is not sensitive to the final prediction model choice. Our predictive model reports a mean of 17,650 miles driven by the household in a year. This is close to the actual "test" data mean of 17,472 miles. As the table shows, we lose some variation in household VMT in the prediction. There is less variation in the LASSO estimated VMT, but this really only affects outliers, as the confidence intervals reported in Appendix Table B1 demonstrate. This table calculates the prediction intervals as a percentage of the prediction means.

3.3 Tract data

Using data from the American Community Survey (ACS 2022) and our "best" fit model, we predict the average household annual vehicle miles traveled at the census tract level (U.S. Census Bureau, 2022). The ACS 2022 provides a wide range of household demographic and socio-economic characteristics per census tract. There are about 80,000 census tracts with an average of 4,000 households per tract. We use a subset of household characteristics that match the information available in NHTS 2017.[7]

[6]The maximum VMT in the test data is a significant outlier. The 99th percentile VMT value is 61,928.

[7]Appendix C reports the coefficients for the variables selected by the "best" fit model, when predicted on the ACS 2022. Note that Urban and Log of income are forced variables in the first step lasso. We believe these two variables are important predictors of household vehicle miles traveled, and, thus, should be included in our predictive models, irrespective of the first step lasso including or excluding these variables.

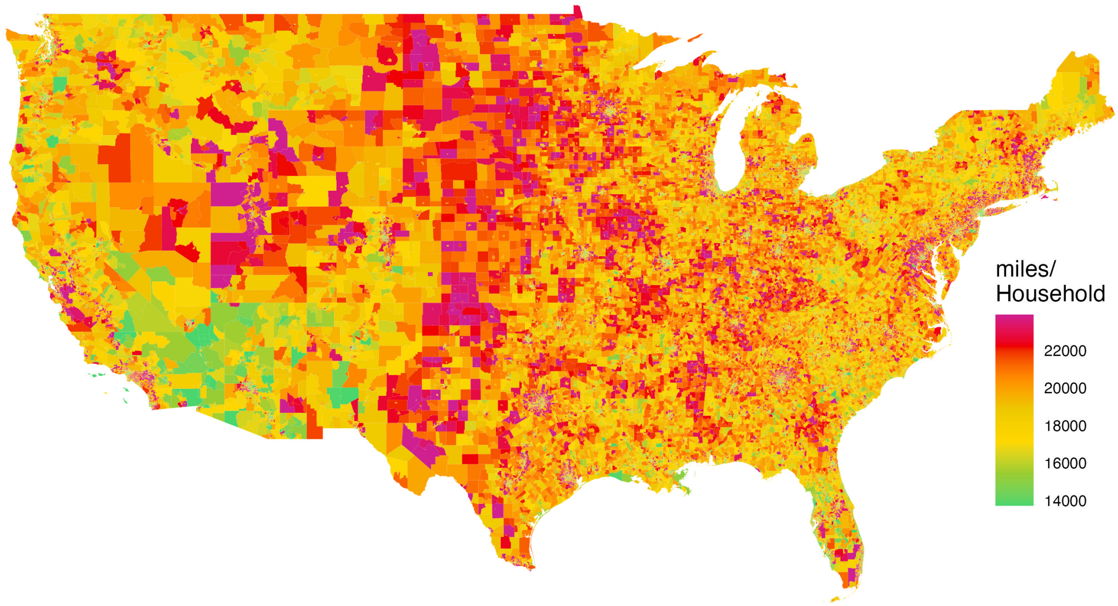


Figure 2: Miles driven by Households in US census tracts, winsorized at 95%.

Figure 2 depicts the predictions for the annual household vehicle miles traveled at the US census tract level.[8] Households along the west coast and portions of the east coast tend to drive fewer miles than the national average, while portions of the Midwest and much of the mountain states average more household vehicle miles traveled.

Next, we add data on the average miles per gallon, which is available at the zip code level.[9] We match the zip codes to census tracts and calculate the average miles per gallon at the census tract level and match this to the ACS 2022 data.[10] Figure 3 shows the variation in average fuel economy across census tracts. More fuel-efficient (higher mpg) vehicles tend to be owned on the two coasts. Combining this information with the VMT information in Figure 2 indicates that more gasoline is consumed by households in the central portion of the country. This follows since gasoline consumption equals vehicle miles traveled divided by fuel efficiency (as measured by miles per gallon):

$$Gas_i = \frac{VMT_i}{MPG_i} \tag{2}$$

where Gas_i is average household gasoline consumption, MPG_i is the tract i average miles per gallon, and VMT_i is the household annual vehicle miles traveled in tract i.

[8] We trim (winsorize) the tracts at the bottom and top 2.5 percent for legibility.

[9] We get these data from the IHS Markit report, frequently referred to as "Polk data."

[10] We use the USPS zip code crosswalk files from the US Department of Housing and Urban Development. (U.S. Department of Housing and Urban Development, 2022)

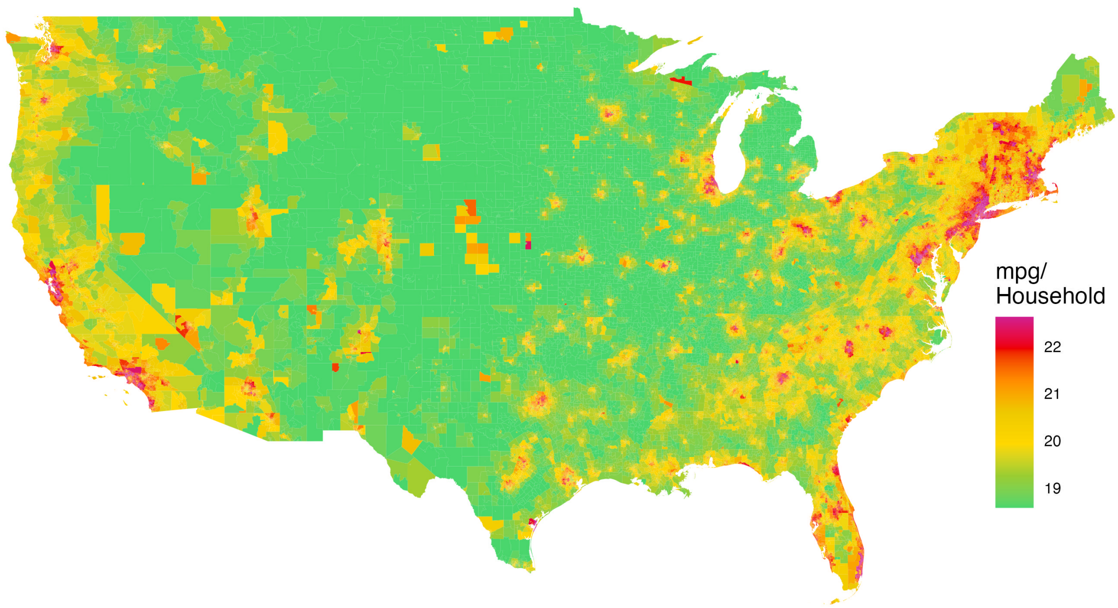


Figure 3: Average miles per gallon for a household in US census tracts, winsorized at 95%.

3.4 Tax Policies

Our thought experiment is to replace the federal gas tax with a vehicle-miles-traveled tax, holding revenue constant. The federal excise tax rate on gasoline is 18.4 cents per gallon.[11] Using the predicted vehicle miles per household for a census tract, we first calculate federal gasoline tax collections for an average household in census tract i as follows:

$$T_i^{Gas} = 0.184 \times Gas_i, \tag{3}$$

where T_i^{Gas} is household gas tax collections in dollars per year and Gas_i is household gasoline consumption in gallons per year.

For the VMT tax, we set the tax rate τ such that it generates the same revenue as the federal gasoline tax, weighting by the number of households in each census tracts (H_i):[12]

$$T^{VMT} \equiv \sum_i \tau VMT_i \times H_i = \sum_i T_i^{Gas} \times H_i \equiv T^{Gas}, \tag{4}$$

where T^{VMT} is aggregate VMT tax collections and T_i^{VMT} is census tract i average household VMT tax

[11]There is a separate tax on diesel fuel for personal motor vehicles. We ignore that in this analysis. We do include the 0.1 cent per gallon gas tax that funds the Leaking Underground Storage Tank (LUST) trust fund.

[12]We ignore behavioral changes in driving or preferences for fuel efficient vehicles in this analysis.

collections (and similarly for the gas tax).

For purposes of assessing the distributional impact of the VMT gas tax swap, we calculate the difference between the gasoline tax (T_i^{Gas}) and the VMT tax (T_i^{VMT}) paid by the households in a census tract, i.e., Δ_i in the following equation:

$$\Delta_i = T_i^{VMT} - T_i^{Gas}. \tag{5}$$

A positive Δ_i indicates that the average household in census tract i pays more in taxes when the VMT tax replaces the gas tax. The next section presents our findings.

4 Results

Given aggregate gas tax collections and an estimate of aggregate vehicle-miles traveled, we calculate the revenue-neutral VMT tax rate to replace federal excise taxes on gasoline to be 0.89 cents per mile. Our predicted household vehicle miles at the census tract level aggregate to the national annual household vehicle miles of 2,310.5 billion for the year 2022. The actual U.S. aggregate household vehicle miles is 2,797.2 billion.[13] The next subsection details our results.

4.1 Gas Tax Collection

Before turning to the distributional analysis, we check to see whether our modeled gas tax collections match actual data. As discussed in Section 3 above, we predict average household miles driven at the census tract level and divide by average fuel economy (miles per gallon) at the tract level to obtain an estimate of average miles driven at the census tract level. Multiplying this by the federal gasoline excise tax rate yields average motor vehicle gas tax revenue at the tract level. We aggregate to the national level (weighting census tracts by population) and obtain predicted federal tax revenue of \$20.6 billion for 2022. This tracks closely to IRS Statistics of Income (SOI) data, which reports average federal excise gasoline tax collections of \$26.2 billion over the years 2018 - 2022, the period covered by our ACS data. (Internal Revenue Service, 2023)

As an additional check on our calculations, we gross up census tract federal gas tax collections to the state level (weighting by census tract population) and compare to state-level federal collections as published in the Federal Highway Administration's annual Highway Statistics publication. (U.S. Department of Transportation Federal Highway Administration, 2022) The FHWA publication tracks at the state level total revenue into the Highway Trust Fund. According to the Congressional Budget Office, the tax on motor

[13] Urban + Rural values in Highway Statistics Series Table VM-1. Data taken from editions covering the years 2018 to 2022.

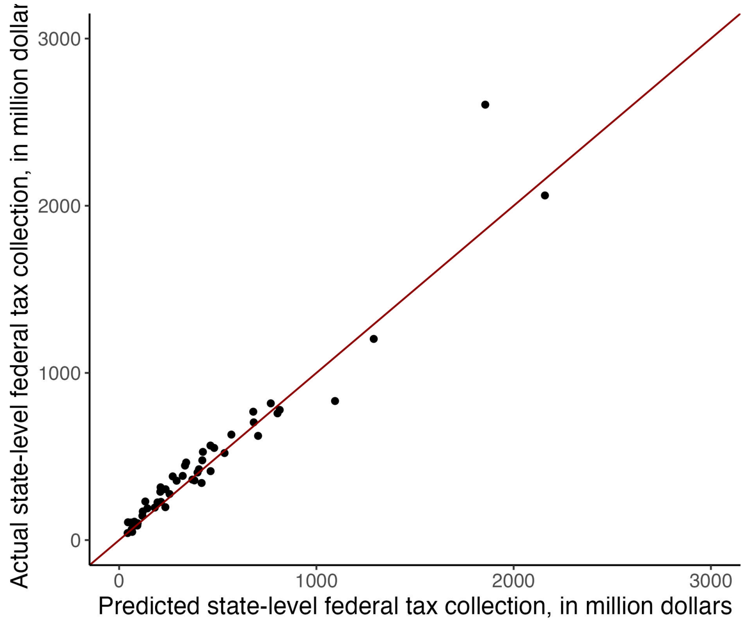
vehicle gasoline consumption accounts for 58.3 percent of total highway trust fund revenue (motor vehicle diesel taxes account for much of the rest). (Congressional Budget Office, 2023b; Urban-Brookings Tax Policy Center, 2023) Applying that percentage rate to the state-level data in the FHWA publication, we compare actual and predicted federal gas tax collections in Figure 4. The fit is quite good, whether plotted in levels (Figure 4a) or in logs (showing percentage differences) (Figure 4b).

4.2 Distributional Implications of a Federal Gas-VMT Tax Swap

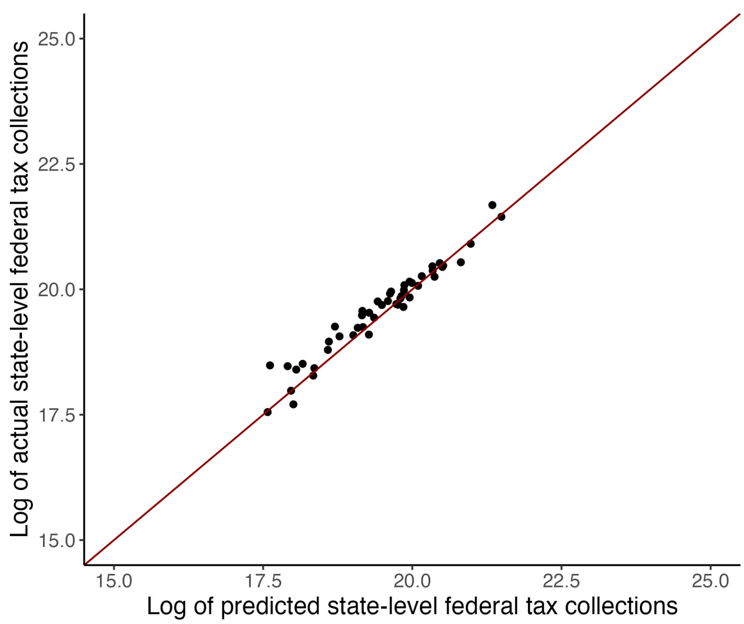
We begin our analysis by showing distributional impacts by income decile. This allows us to compare our results to the results in previous distributional analyses of a Gas VMT tax swap. Figure 5 shows the distributional impact for the entire sample (upper left) and broken out by types of areas. Focusing on the overall impact (upper left), the figure shows for each decile a box and whisker plot showing the mean value and the inter-quartile range. While within each decile, there are tracts with tax increases and decreases, the figure shows that, on average, the tax swap is mildly progressive, with the mean amount of the tax increase increasing with income, as is the proportion of tracts with positive tax changes. Our results accord with results from Glaeser et al. (2023) and Metcalf (2023).

Breaking out results by type of census tract leads to interesting results. Most rural tracts experience a decline in tax payments, though there is a sharp rise in the top income decile, with most tracts in that decile paying more in taxes. The story for metropolitan tracts is similar to the overall story, while suburban areas look similar to rural areas (except in the top decile).

Figure 4: Actual and Predicted Federal Gas Tax Revenue at State Level



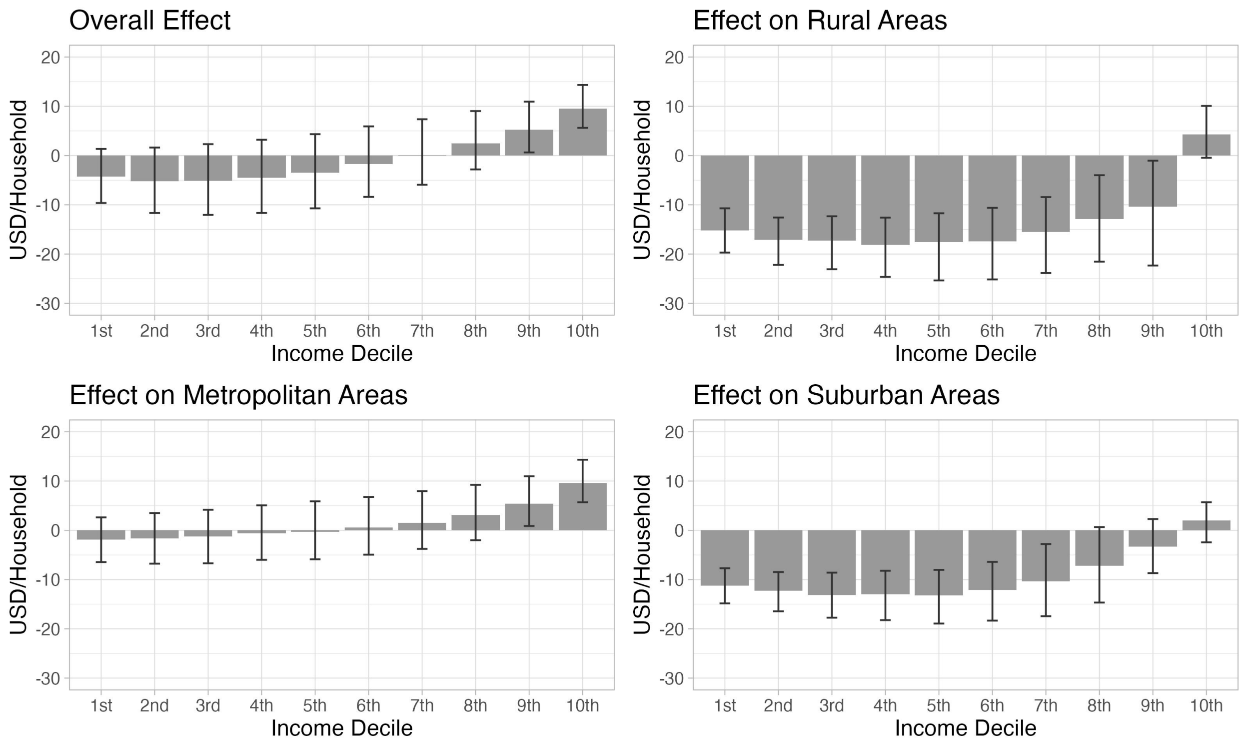
(a)



(b)

Note: Panel (a) reports actual versus predicted gas tax collection in levels. Panel (b) reports the log of revenues. Red line represents 45°line. Data: Highway Statistics Series 2018-2022. Revenue from gas tax collection is about 58% of the total payments into the Highway Trust Fund as reported in Table FE-221B.

Figure 5: Change in tax payments by income decile and urbanity



Note: See text for definition of the areas.

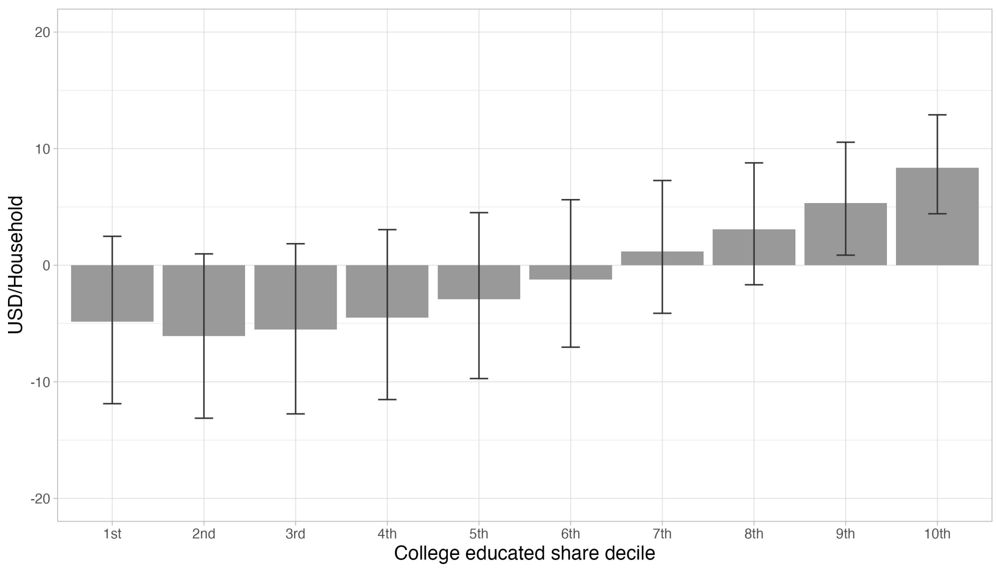
Our results above show changes in tax collections across income groups. Tax progressivity is traditionally defined in terms of the income-related pattern of changes in tax burden as a share of income. A tax reform that leads to a change in tax burden as a share of income rising with income is said to be progressive. If the burden as a share of income falls as income rises, the tax is regressive. In the appendix, we provide figures depicting the change in driving-related tax burden as a percentage of household income for various cuts of the data. We find that the pattern across income groups looks similar whether we are measuring changes in tax burden or changes in tax burden relative to income.

Tax-incidence analysis has long focused on the question of how to sort people by some intrinsic measure of well-being (aptitude, ability to earn, etc). A highly able individual might have the ability to earn a high income, but choose to work less and consume more leisure. We should not group that individual with a lower ability individual who works two jobs to earn the same income as the more able, but less hardworking individual. As the example highlights, annual income is an imperfect proxy for well-being, and researchers have long understood that it can bias distributional analyses of excise taxes in a regressive direction.[14] Lifetime income would be a better measure of well-being, but this is unobservable. Researchers

[14]Differences between transitory and permanent income can also bias distributional analyses as discussed by, among others, Poterba (1991) and Metcalf (1999)

have constructed measures of lifetime income (Caspersen and Metcalf (1994), for example) or used current consumption as a proxy (Poterba (1991), Metcalf (1999)), among others). Another possibility is to use education as a proxy for lifetime income. We take that approach here by ranking census tracts by the percentage of college-educated households in each tract. When we do that (Figure 6), we find that the tax swap does not look appreciably different. It is still modestly progressive, with the proportion of tracts showing positive tax changes rising with the proportion of college-educated households in the tract.

Figure 6: Change in tax payments by college education

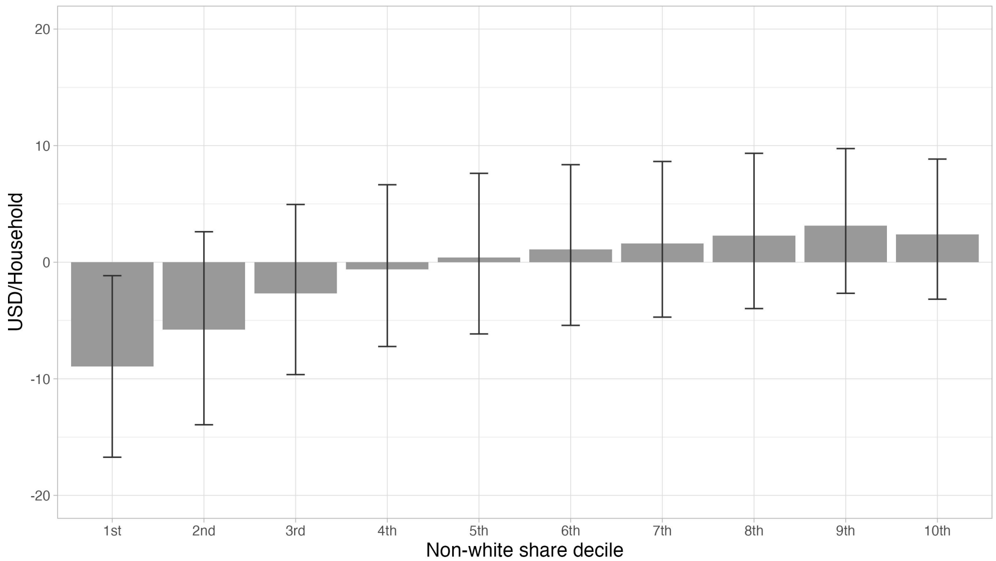


Note: Change in tax payments by deciles of percentage of college-educated households in a census tract.

As another cut of the data by demographics, we consider the change in tax payments when we sort tracts by the share of non-white households in the tract.[15] Figure 7 shows that the change in tax burden is positively correlated with the share of non-white households. The median change in tax payments is negative for the first three deciles and positive for the remaining seven. This reflects the tendency for non-white households to congregate disproportionately in urban areas and along the two coasts.

[15]Household race is defined by the self-reported race of the household head.

Figure 7: Change in tax payments by race



Note: Change in tax payments by deciles of percentage of non-white households in a census tract.

The results discussed so far confirm the results of previous research. We next turn to new results where we focus on distributional impacts along geographic and political dimensions. Table 1 reports the share of census tracts (weighted by population) that experience either an increase or decrease in tax payments from a VMT gas tax swap. At the national level, the swap raises taxes for roughly 55 percent of households. Figure 8 shows that the census tracks on the two coasts are more likely to experience an increase in taxation, while those in the middle of the country are more likely to experience a decrease.[16] By construction, the mean change in tax payments across census tracts is zero. The median change is \$1.14 while tax revenue changes vary from a minimum of -\$51.43 to a maximum of \$46.43. The full range includes a few large outliers; the interquartile range is \$14.19 (-\$6.65 to \$7.54) and the standard deviation is \$9.97.[17]

[16]Higher tax payments are also correlated with EV and PHEV ownership within census tracts. In Appendix E.3, we plot the average change in driving-related taxes from the gas-VMT tax swap against EV and PHEV ownership shares at the tract level. Not surprisingly, higher penetration of EV and PHEV vehicles in a census tract is associated with higher tax payments in those tracts across the range of ownership shares typically experienced in the data.

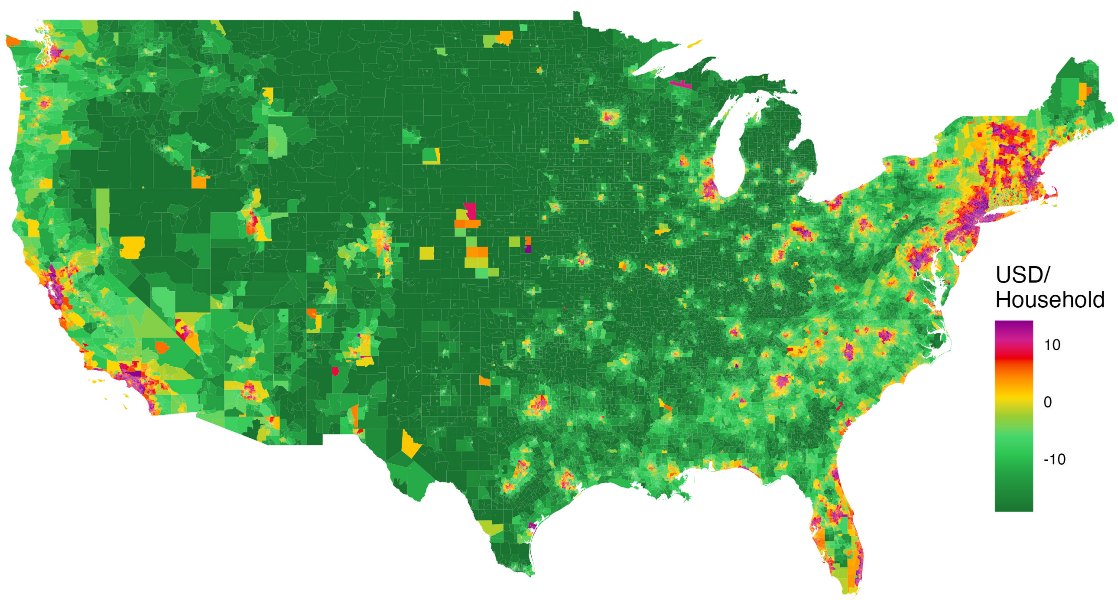
[17]All summary statistics are weighted by the number of households in each census tract.

Table 1: Regional Impact of Gas-VMT Tax Swap

	Tax Increase	Tax Decrease
US	0.55	0.45
New England	0.81	0.19
Middle Atlantic	0.83	0.17
South Atlantic	0.63	0.37
East North Central	0.34	0.66
West North Central	0.23	0.77
East South Central	0.19	0.81
West South Central	0.34	0.66
Mountain	0.44	0.56
Pacific	0.79	0.21

Note: Table reports the population weighted share of census tracts experiencing a tax increase or decrease.

Figure 8: Changes in tax collections from Gas-VMT swap



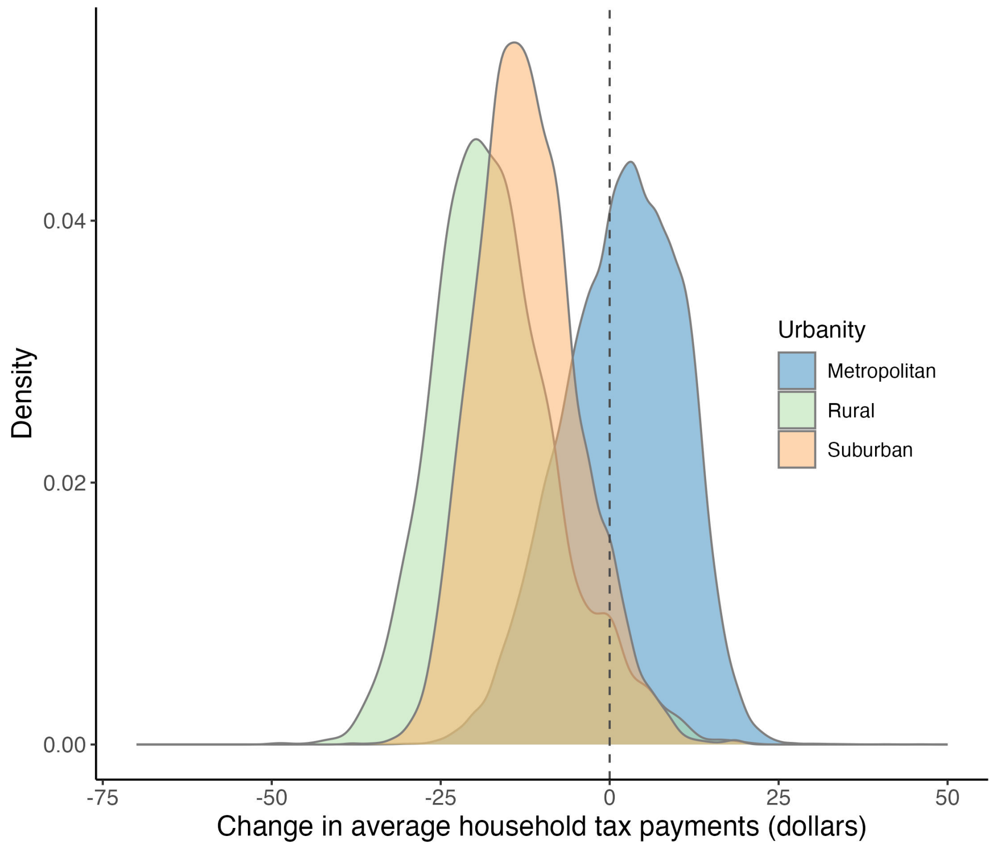
Note: Census tract average data are winsorized at 95%.

Figure 9 shows a density plot of the change in average household tax collections at the tract level when distinguishing between metropolitan, suburban, and rural tracts.[18] The distribution for changes in tax

[18]Our measure of urbanity is based on the U.S. Department of Agriculture Economic Research Service definition

payments is quite similar between rural and suburban tracts, with most tracts experiencing a decline in tax payments. The density curve for urban tracts, in contrast, is shifted significantly to the right.

Figure 9: Change in tax collections from gas-VMT tax swap tax by urbanity.



Note: See text for definition of urbanity groups.

We next turn to an analysis by political affiliation. The geographic results presented above suggest that census tracts with Republican voters are likely to pay lower taxes with this tax swap, while tracts with Democratic voters are likely to pay more. We explore that explicitly here. Figure 10 shows density functions for changes in tax payments by the political affiliation of the census tract's member of the U.S. House of Representatives. There is a clear difference in the distribution of changes in tax payments, with the distribution for Democratic tracts shifted significantly to the right.

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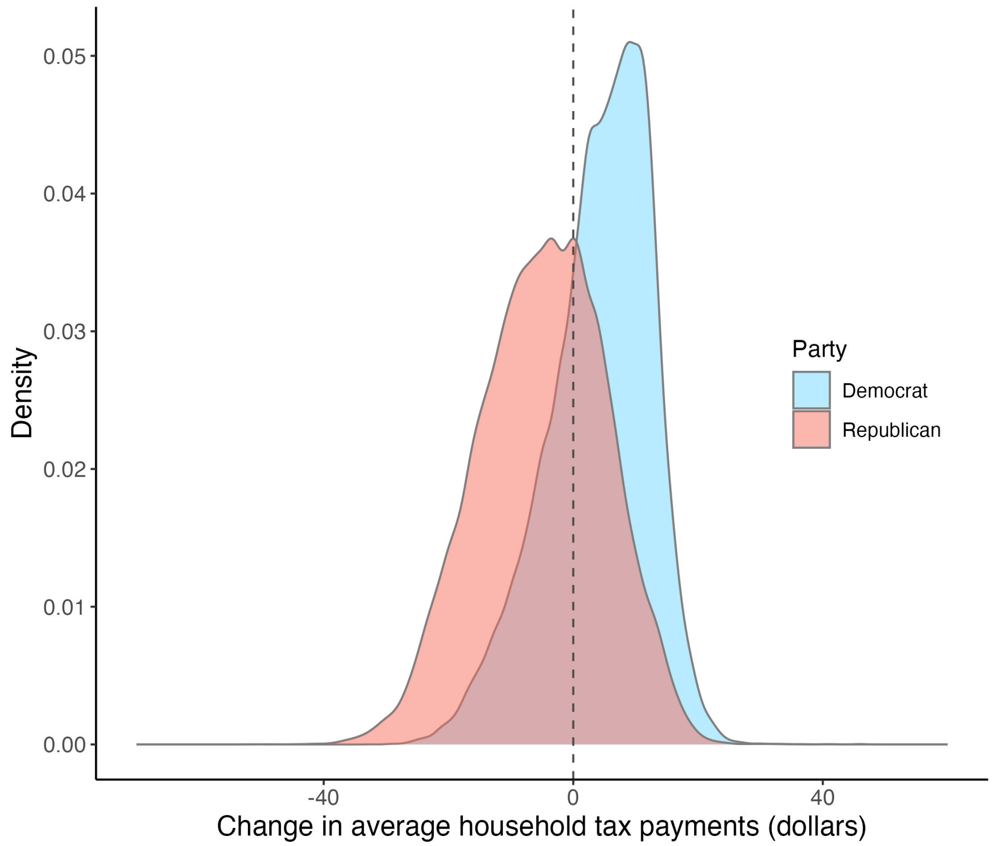
of Rural Urban continuum codes for U.S. counties. 2023 Rural-Urban Continuum Codes used. (U.S. Department of Agriculture Economic Research Service, 2023) Metropolitan counties are all counties in metro areas. Suburban counties are the ones adjacent to metro areas. Finally, rural counties are the ones not adjacent to metro areas. All census tracts in a county are marked metropolitan, suburban, or rural based on these codes.

Figure 10: Change in tax collections from gas-VMT tax swap by political party affiliation



Note: Party affiliation based on affiliation of the House Members in the 118th Congress

Table 2 shows the proportion of tracts (weighted by population) with tax increases and decreases based on the affiliation of the Congressional representative. Over three-quarters of households with Democratic representatives experience an increase in tax payments, while nearly three-quarters of Republican tracts experience a tax decrease.

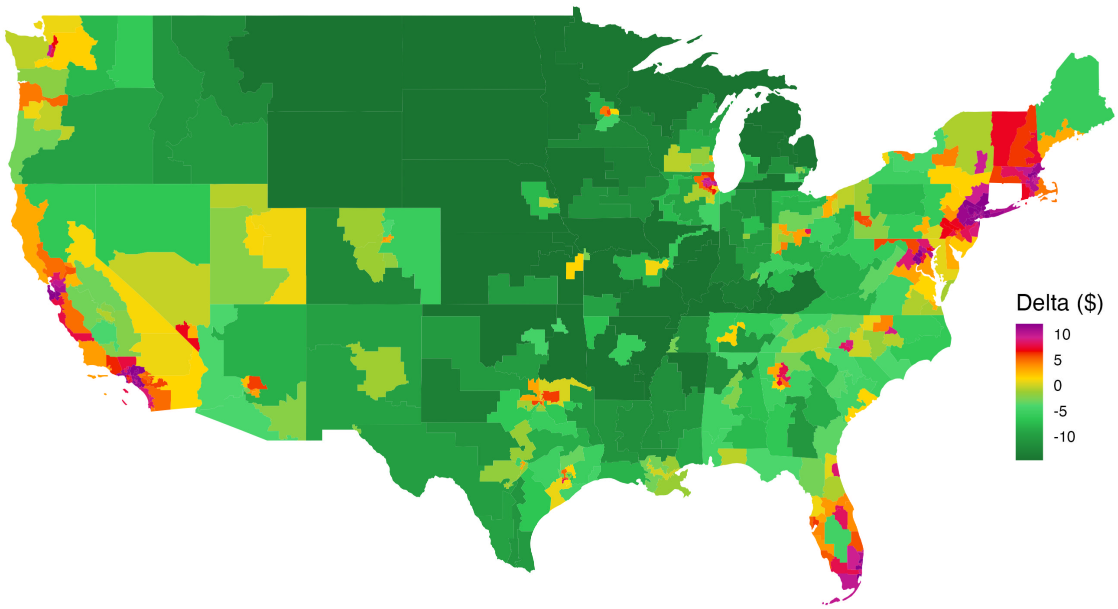
Table 2: Tax changes by political affiliation

	Tax Increase	Tax Decrease	Population
Republican	0.282	0.718	0.499
Democrat	0.770	0.230	0.498
Independent	0.275	0.725	0.002

Note: Table reports census tracts, weighted by population, with tax increases or decreases by party affiliation of Congressional representative.

We also graphically show tax changes from the tax swap aggregated to the Congressional District level. Figure 11 illustrates that bi-coastal Congressional districts predominantly face higher taxes while districts in the middle of the country benefit from lower tax payments.

Figure 11: Change in tax collections from gas-VMT swap by Congressional District

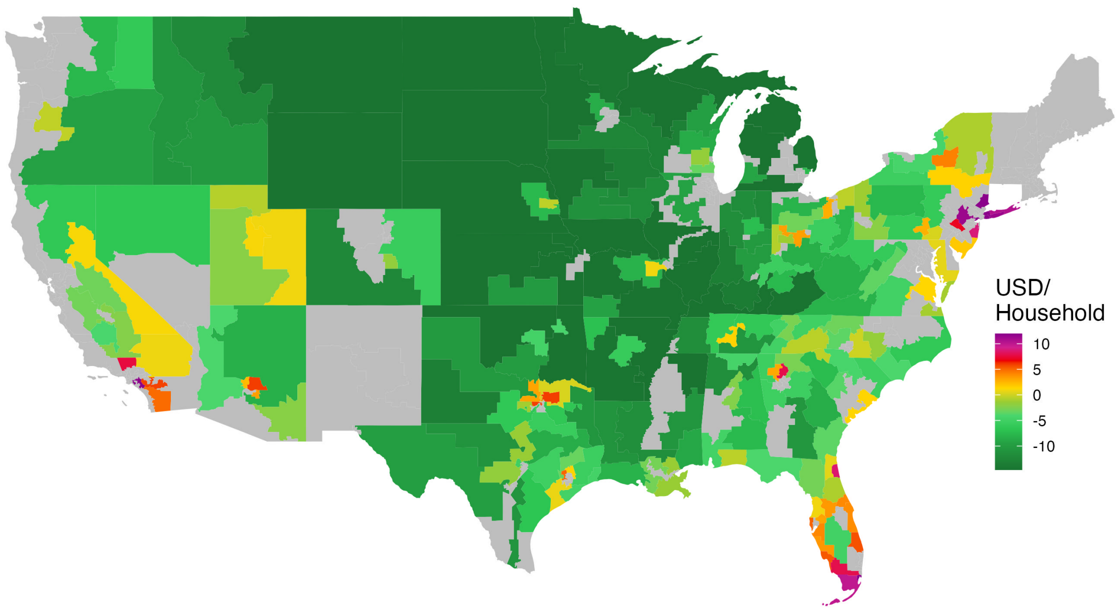


Note: Congressional district data are winsorized at 95%.

To emphasize the variation within political affiliation, we also present figures conditional on Congressional representation. Figures 12 and 13 show variation within Republican and Democratic districts, respectively. The few Republican districts with increases in tax payments due to the swap are in California, Florida, and the New York metropolitan area. Democratic-aligned tracts with tax decreases are scattered around the United States, but mostly in the central portions of the country.[19]

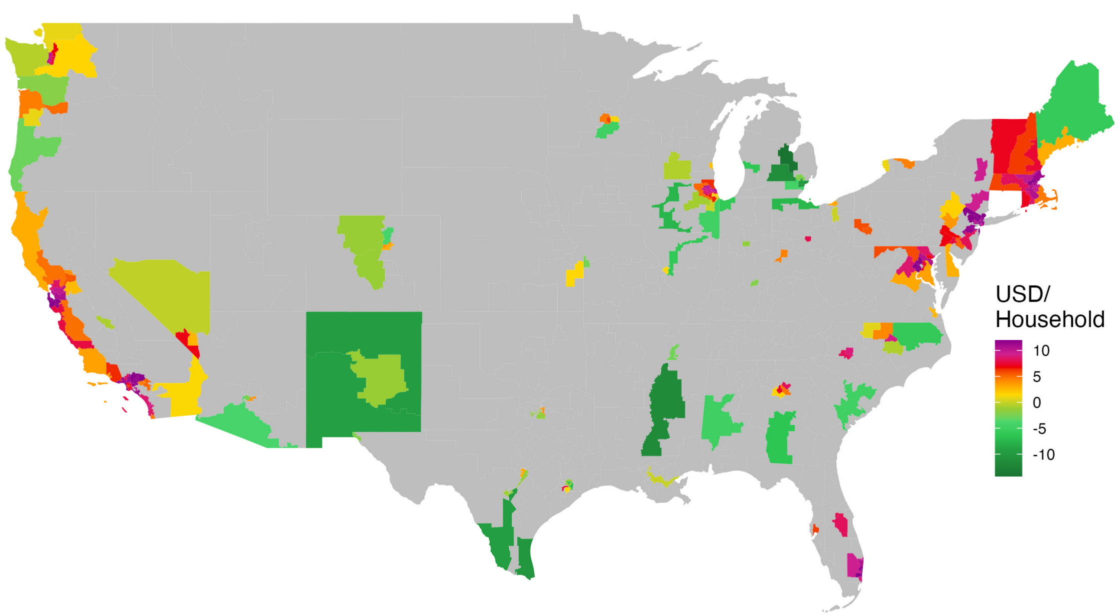
[19] Appendix E1 combines these two figures into a single figure.

Figure 12: Change in tax collections from gas-VMT swap for Republican Congressional Districts



Note: Data are winsorized at 95%.

Figure 13: Change in tax collections from gas-VMT swap for Democratic Congressional Districts



Note: Data are winsorized at 95%.

5 Conclusion

Using machine learning techniques, we estimate average household vehicle miles traveled at the census tract level. This allows us to provide a highly disaggregated analysis of the distributional impacts of a tax swap where the federal excise tax on gasoline for motor vehicles is replaced with a vehicle miles traveled tax. Our results on the distributional impacts by income confirm results from previous studies, albeit with more recent data. We then go on to provide results showing the distributional impact across geographic regions as well as political affiliation. The most striking result of this analysis is the distinct benefit this tax swap provides to rural and lower-income census tracts, including those in the middle of the country.

Our focus here has been on the distributional implications of a tax swap to address the ongoing erosion of the tax base of the motor vehicle fuel excise tax. We should emphasize that we have not made a case on theoretical grounds for efficiency improvements from such a tax swap. Whether we should think of the gas (or VMT) tax as a benefit tax or as an externality-correcting tax, there are a number of factors to take into consideration. A benefits perspective argues for a VMT tax on the grounds that those using roads should bear the cost of their upkeep (as financed through the Highway Trust Fund). But this begs the question of the appropriate sharing of costs between personal and commercial transportation, and especially long-haul trucking in the latter category. From an externalities perspective, considerations of local pollution, road wear, congestion, and accidents all come into play. Innovation and network failures that impede the penetration of electric vehicles are also a consideration. We leave that analysis for future research.

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A Model Selection

Table A1: Predicting Annual Household Vehicle Miles Traveled

Model	LASSO Prediction			OLS Prediction		
	OOS test R^2	OOS train R^2	OOS test adj. R^2	OOS test R^2	OOS train R^2	OOS test adj. R^2
	(1)	(2)	(3)	(4)	(5)	(6)
Level, base, λ.1se	0.2327	0.2327	0.2325	0.2499	0.2500	0.2497
Level, sq, λ.1se	0.2330	0.2330	0.2328	0.2499	0.2500	0.2497
Level, int, λ.1se	0.2344	0.2344	0.2342	0.2499	0.2500	0.2497
Level, sq int, λ.1se	0.2345	0.2345	0.2343	0.2499	0.2500	0.2497
Level, base, λ.min	*0.2662*	*0.2662*	*0.2656*	*0.2656*	*0.2656*	*0.2651*
Level, sq, λ.min	0.2661	0.2662	0.2656	0.2656	0.2656	0.2651
Level, int, λ.min	0.2659	0.2659	0.2652	0.2648	0.2648	0.2642
Level, sq int, λ.min	0.2659	0.2659	0.2652	0.2648	0.2648	0.2642
Log, base, λ.1se, leveled	0.1634	0.1634	0.1632	0.1842	0.1842	0.1841
Log, sq, λ.1se, leveled	0.1634	0.1634	0.1632	0.1842	0.1842	0.1841
Log, int, λ.1se, leveled	0.1635	0.1635	0.1633	0.1847	0.1847	0.1846
Log, sq int, λ.1se, leveled	0.1635	0.1635	0.1633	0.1847	0.1847	0.1846
Log, base, λ.min, leveled	0.1989	0.1989	0.1984	0.1985	0.1985	0.1979
Log, sq, λ.min, leveled	0.1989	0.1989	0.1984	0.1985	0.1985	0.1979
Log, int, λ.min, leveled	0.1988	0.1988	0.1982	0.1983	0.1983	0.1978
Log, sq int, λ.min, leveled	0.1988	0.1988	0.1982	0.1983	0.1983	0.1978

Note: This table reports out-of-sample R-squared statistics on the test and train data for the 32 models considered: LASSO and OLS prediction models, λ_{min} and λ_{1se}, dependent variable in levels and logs, independent variables in linear form (base), linear and quadratic (sq), with interactions among variables in linear form (int), and interactions in linear and quadratic form (sq int). The final selected model is shown in *italics*.

Table A2: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Median	Max
Test data	33,683	17,472	13,472	0	14,376	241,619
Predicted, Adaptive Lasso	33,683	17,650	7,142	1,920	17,384	40,373
Predicted, OLS	33,683	17,604	7,206	1,204	17,312	41,273

Note: Actual and predicted data by best fit model for household annual vehicle miles traveled model.

B Prediction Confidence Intervals as a % of Prediction Means

Table B1: Model evaluation for *household annual vehicle miles traveled.*

Model	Adaptive LASSO				OLS			
	2.5% CI_P	97.5% CI_P	$\bar{P}$	$\frac{\Delta CI_P}{\bar{P}} \times 100$	2.5% CI_P	97.5% CI_P	$\bar{P}$	$\frac{\Delta CI_P}{\bar{P}} \times 100$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Level, base, λ.1se	18298.78	18432.17	18365.48	0.73	17864.41	18015.45	17939.93	0.84
Level, sq, λ.1se	18295.46	18428.92	18362.19	0.73	17864.41	18015.45	17939.93	0.84
Level, int, λ.1se	18270.59	18404.71	18337.65	0.73	17864.41	18015.45	17939.93	0.84
Level, sq int, λ.1se	18269.22	18403.37	18336.29	0.73	17864.41	18015.45	17939.93	0.84
Level, base, λ.min	*17574.22*	*17726.76*	*17650.49*	*0.86*	*17527.29*	*17681.20*	*17604.24*	*0.87*
Level, sq, λ.min	17573.66	17726.20	17649.93	0.86	17527.29	17681.20	17604.24	0.87
Level, int, λ.min	17528.02	17682.16	17605.09	0.88	17504.60	17659.92	17582.26	0.88
Level, sq int, λ.min	17527.77	17681.92	17604.84	0.88	17504.60	17659.92	17582.26	0.88
Log, base, λ.1se	14304.57	14425.33	14364.95	0.84	20668.86	20872.53	20770.70	0.98
Log, sq, λ.1se	14304.57	14425.33	14364.95	0.84	20668.86	20872.53	20770.70	0.98
Log, int, λ.1se	14302.50	14423.28	14362.89	0.84	20675.73	20879.80	20777.77	0.98
Log, sq int, λ.1se	14302.50	14423.28	14362.89	0.84	20675.73	20879.80	20777.77	0.98
Log, base, λ.min	13904.30	14046.70	13975.50	1.02	20198.84	20408.83	20303.84	1.03
Log, sq, λ.min	13904.30	14046.70	13975.50	1.02	20198.84	20408.83	20303.84	1.03
Log, int, λ.min	13905.04	14047.46	13976.25	1.02	20200.01	20410.02	20305.01	1.03
Log, sq int, λ.min	13905.04	14047.46	13976.25	1.02	20200.01	20410.02	20305.01	1.03

Note: This table reports prediction confidence interval (ΔCI_P) as a percentage of prediction mean ($\bar{P}$) for Adaptive LASSO (Columns (1) to (4)) and OLS (Columns (5) to (8)) models, choice of λs, choice of dependent variable in logs and levels, choice of independent variable matrix including base variables, squares, interactions, and both squares and interactions. Columns (1), (2), (5), and (6) show the 2.5% and 97.5% confidence intervals for the Adaptive LASSO and OLS predictions, respectively. Columns (3) and (7) report the mean predictions from the Adaptive LASSO and OLS models, respectively. Finally, Columns (4) and (8) report the prediction confidence intervals as a percentage of prediction means, i.e., $\frac{\Delta CI_P}{\bar{P}} \times 100$, where $\Delta CI_P = 97.5\% CI_P - 2.5\% CI_P$, for the Adaptive LASSO and OLS models, respectively. Best fit model shown in *italics*.

C Variable Selection

Table C1: Variables selected: Vehicle Miles. Note: (.) denotes variables not selected by the predictive model.

Variable	Vehicle Miles (miles)
Intercept	1845.26
Division East North Central	
Division East South Central	887.57
Division Middle Atlantic	.
Division Mountain	.
Division New England	.
Division Pacific	.
Division South Atlantic	.
Division West North Central	.
Division West South Central	.
Region Midwest	.
Region Northeast	.
Region South	.
Region West	-1501
Household: Race American Indian Alaska Native	.
Household: Race Asian	.
Household: Race Black	.
Household: Race Mixed	.
Household: Race Native Hawaiian Pacific Islander	.
Household: Race Other	1851.6
Household: Race White	.
Household: Age 35 To 44	.
Household: Age 45 To 54	.

Continued on next page

Table C1: Variables selected: Vehicle Miles. Note: (.) denotes variables not selected by the predictive model. (Continued)

Household: Age 55 To 64	.
Household: Age 65 To 74	-1309.52
Household: Age 75 To 84	-2265.21
Household: Age Above 85	-3229.6
Household: Age Under 35	.
Household: Education Bachelors or Higher	665.06
Household: Education Below High School	2152.91
Household: Education High School	.
Household: Education Some College	.
Household: Vehicles None	.
Household: Vehicles 1	-4200.43
Household: Vehicles 2	.
Household: Vehicles 3 or More	5071.46
To Work by Bicycle	-5945.08
To Work by Cab	3784.07
To Work by Car	.
To Work by Home	.
To Work by Public Transport	-4918.94
To Work by Walk	-4665.39
Household: Size 1	-1448.19
Household: Size 2	.
Household: Size 3	1693.97
Household: Size 4 or More	3233.72
Household: Employed 1	.
Household: Employed 2	2838.68

Continued on next page

Table C1: Variables selected: Vehicle Miles. Note: (.) denotes variables not selected by the predictive model. (Continued)

Household: Employed 3	5674.03
Household: Employed 4 or More	9126.49
Household: Employed None	-1930.89
Miles per gallon	.
Owner Occupied Housing Units	.
Metropolitan	-1513.69
Suburban	.
Urban	-1878.46
Household: Hispanic Latino	.
Log of Income	1693.33

D Policy Tables

Urbanity	Policy	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Total	Gas Tax	-143.2780	-155.2913	-159.7528	-162.4248	-164.3859	-165.1462	-166.6645	-167.7863	-171.7481	-175.3432
Total	VMT Tax	-139.7121	-150.7284	-155.3634	-158.6665	-161.5515	-163.8511	-167.0110	-170.4529	-176.9802	-184.8270
Total	Gas VMT Swap δ	-3.5659	-4.5629	-4.3894	-3.7583	-2.8345	-1.2951	0.3464	2.6666	5.2321	9.4838
Total	Gas VMT Swap Rate	-0.0110	-0.0100	-0.0082	-0.0062	-0.0042	-0.0017	0.0004	0.0027	0.0045	0.0057
Metropolitan	Gas Tax	-135.1843	-145.2236	-150.1285	-153.2819	-157.2309	-160.0722	-163.3192	-166.4192	-171.3274	-175.2585
Metropolitan	VMT Tax	-133.9497	-143.9911	-149.2045	-152.9504	-157.1460	-160.7270	-164.9250	-169.5790	-176.7106	-184.7677
Metropolitan	Gas VMT Swap δ	-1.2346	-1.2325	-0.9240	-0.3315	-0.0849	0.6548	1.6059	3.1598	5.3832	9.5092
Metropolitan	Gas VMT Swap Rate	-0.0038	-0.0027	-0.0017	-0.0005	-0.0001	0.0009	0.0019	0.0032	0.0046	0.0057
Rural	Gas Tax	-187.2410	-196.6840	-200.6876	-204.9254	-208.0052	-211.3461	-213.9239	-213.2545	-220.7869	-203.7519
Rural	VMT Tax	-172.6121	-180.2657	-184.0013	-187.4768	-191.0402	-194.3801	-198.5411	-200.5928	-209.7803	-208.6240
Rural	Gas VMT Swap δ	-14.6289	-16.4183	-16.6863	-17.4486	-16.9650	-16.9660	-15.3827	-12.6617	-11.0066	4.8721
Rural	Gas VMT Swap Rate	-0.0438	-0.0360	-0.0310	-0.0287	-0.0249	-0.0224	-0.0181	-0.0130	-0.0094	0.0030
Suburban	Gas Tax	-166.3486	-174.7819	-179.9593	-183.9389	-187.0908	-190.1284	-193.1036	-192.6820	-192.2754	-192.2906
Suburban	VMT Tax	-155.2679	-162.7755	-167.1245	-171.0976	-174.3488	-178.3458	-182.7346	-185.9760	-189.3613	-195.2649
Suburban	Gas VMT Swap δ	-11.0807	-12.0064	-12.8348	-12.8413	-12.7420	-11.7826	-10.3690	-6.7059	-2.9141	2.9744
Suburban	Gas VMT Swap Rate	-0.0328	-0.0263	-0.0239	-0.0211	-0.0187	-0.0155	-0.0122	-0.0069	-0.0025	0.0020

Table D1: Change in tax collections from gas-VMT swap by Income Decile and Urbanity

Urbanity	Policy	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11
Total	Gas Tax	-112.2675	-113.9302	-129.4050	-142.3208	-153.6437	-162.5447	-166.4765	-170.2401	-175.1000	-175.0028	-175.8655
Total	VMT Tax	-112.7144	-113.1302	-127.6199	-138.8869	-149.1476	-159.1051	-166.9911	-174.6705	-182.2328	-184.9169	-189.0282
Total	Gas VMT Swap δ	0.4469	-0.8000	-1.7851	-3.4339	-4.4962	-3.4395	0.5146	4.4304	7.1328	9.9141	13.1627
Total	Gas VMT Swap Rate	0.0058	-0.0061	-0.0084	-0.0111	-0.0103	-0.0055	0.0006	0.0040	0.0052	0.0059	0.0058
Metropolitan	Gas Tax	-112.4104	-112.0325	-123.5450	-134.7813	-143.8544	-154.4013	-163.3231	-169.6104	-174.8747	-174.9634	-175.8414
Metropolitan	VMT Tax	-112.8578	-111.4398	-123.2877	-133.5117	-142.5318	-154.0684	-165.0755	-174.2880	-182.0646	-184.8928	-189.0104
Metropolitan	Gas VMT Swap δ	0.4475	-0.5926	-0.2573	-1.2696	-1.3226	-0.3329	1.7524	4.6776	7.1899	9.9294	13.1690
Metropolitan	Gas VMT Swap Rate	0.0058	-0.0045	-0.0012	-0.0041	-0.0030	-0.0005	0.0020	0.0042	0.0053	0.0059	0.0058
Rural	Gas Tax	0.0000	-145.3882	-177.3773	-186.8395	-195.0255	-204.6835	-212.9059	-219.2664	-216.5412	-194.9877	-203.2473
Rural	VMT Tax	0.0000	-142.7081	-165.3014	-172.1235	-178.9139	-187.6480	-197.4634	-205.9561	-213.4371	-201.5489	-214.0707
Rural	Gas VMT Swap δ	0.0000	-2.6800	-12.0759	-14.7160	-16.1116	-17.0356	-15.4425	-13.3104	-3.1041	6.5612	10.8234
Rural	Gas VMT Swap Rate	0.0000	-0.0190	-0.0559	-0.0475	-0.0368	-0.0278	-0.0185	-0.0122	-0.0023	0.0039	0.0043
Suburban	Gas Tax		-144.7450	-152.7893	-164.3514	-173.7211	-183.8109	-192.3689	-191.5797	-198.4199	-183.1963	-197.0133
Suburban	VMT Tax		-139.8789	-143.6135	-153.7328	-161.7523	-171.1143	-181.8529	-187.0010	-199.5109	-188.0099	-197.8203
Suburban	Gas VMT Swap δ		-4.8662	-9.1757	-10.6186	-11.9688	-12.6967	-10.5160	-4.5787	1.0910	4.8136	0.8070
Suburban	Gas VMT Swap Rate		-0.0381	-0.0417	-0.0341	-0.0274	-0.0207	-0.0125	-0.0043	0.0008	0.0029	0.0004

Table D2: Change in tax collections from gas-VMT swap by Income Group and Urbanity

E Other Figures

E.1 Congressional District Impacts

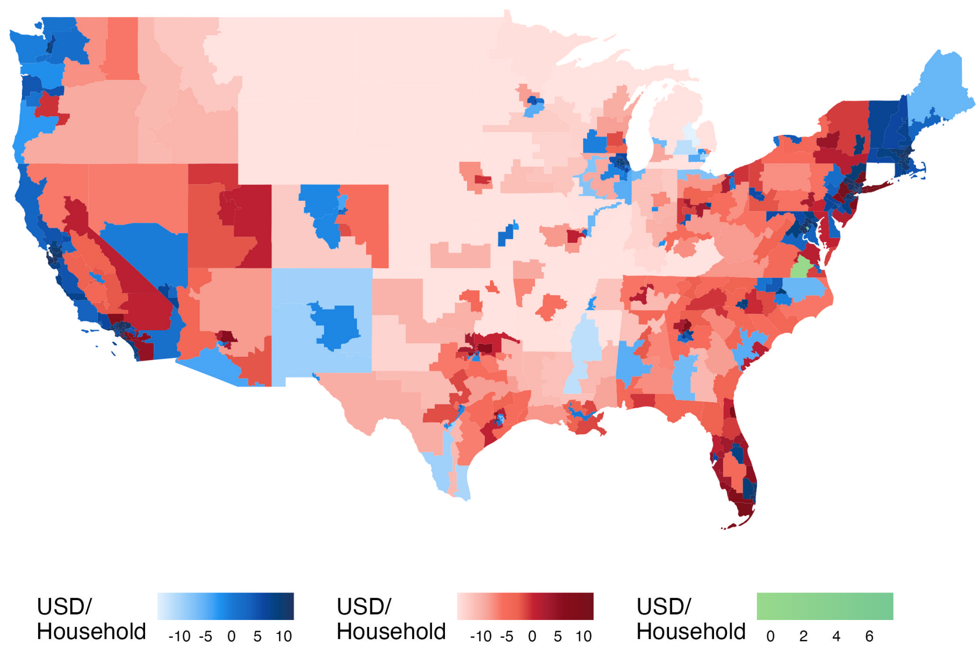
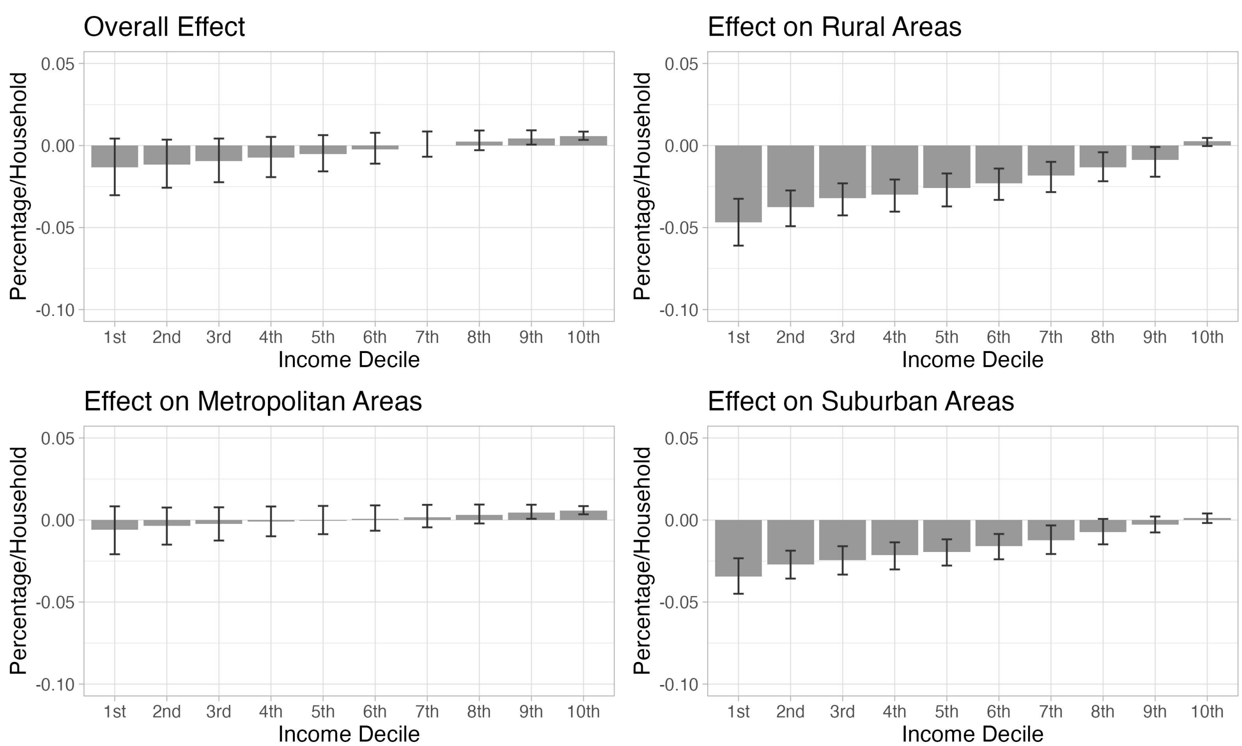


Figure E1: Change in tax collections from gas-VMT swap by 118^{th} Congressional District and party affiliation, winsorized at 95%. (Republican as red, Democrat as blue, and Independent as green.)

E.2 Distributional Figures using Change in Burden to Income

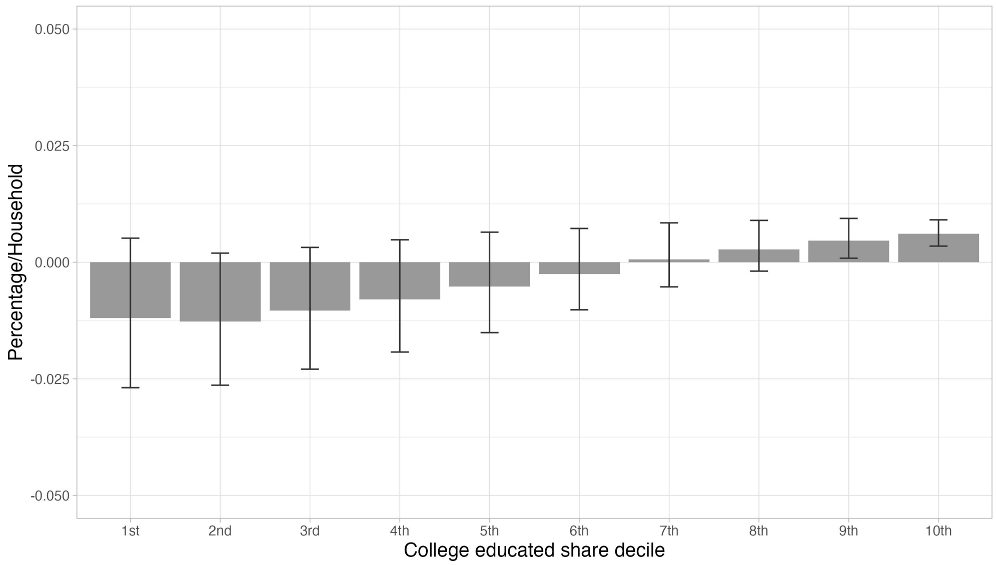
We include here additional distributional charts where we graph the change in tax burden as a share of household income across different demographic characteristics. The patterns in the figure mimic the patterns when graphing the change in tax payments across these demographic characteristics.

Figure E2: Change in tax payments as a percentage of income by income decile and urbanity



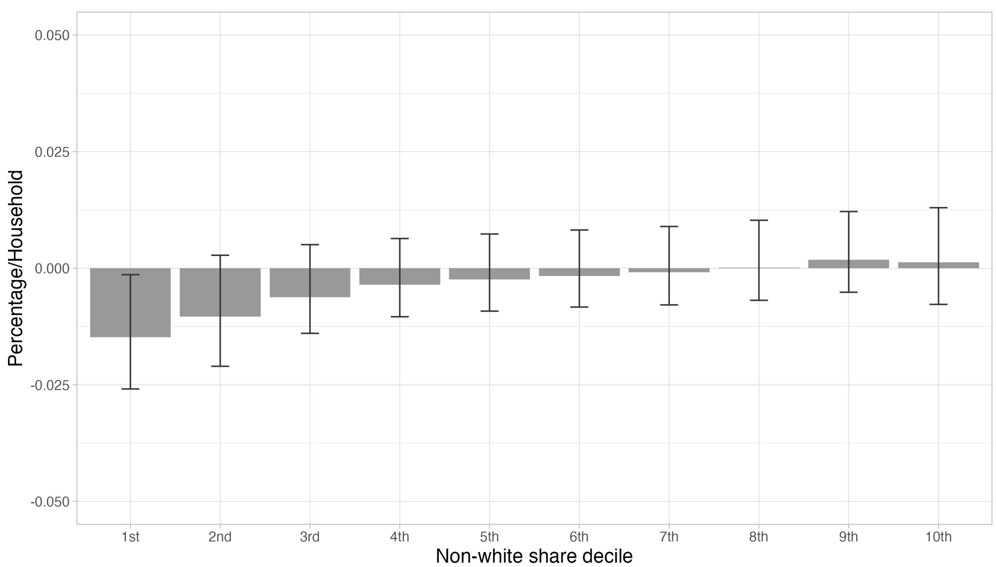
Note: See text for definition of the areas.

Figure E3: Change in tax payments as a percentage of income by college education



Note: Change in tax payments as a percentage of income by deciles of percentage of college-educated households in a census tract.

Figure E4: Change in tax payments as a percentage of income by race

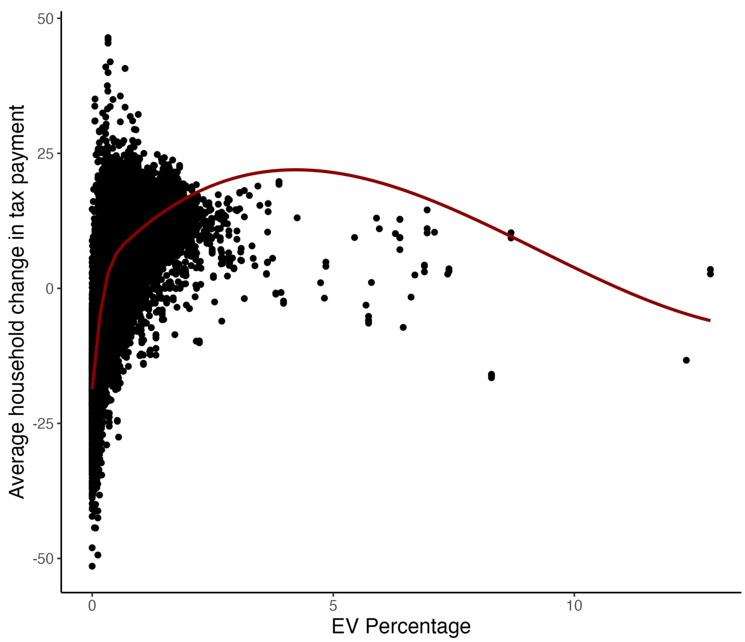


Note: Change in tax payments as a percentage of income by deciles of percentage of non-white households in a census tract.

E.3 Relation of EV and PHEV Ownership and Change in Tax Payments

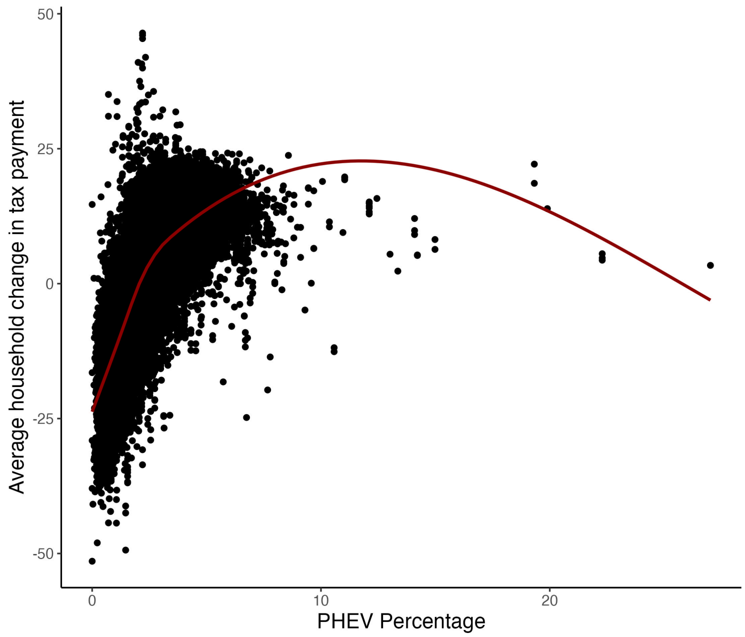
While electric vehicles (EVs) and plug-in hybrid vehicles (PHEVs) are a small fraction of vehicles owned by households, we do a check to see if there is a relationship between the change in tax payments and EV or PHEV ownership. Figure E5 displays a scatterplot along with a lowess plot of the change in tax payments from the tax swap against the percentage of EVs owned by households within a census tract. Over the support of the data, there is a strong positive correlation between EV penetration at the census tract level and the change in tax payments. Figure E6 shows the same positive relation for PHEVs.

Figure E5: Change in tax payments by electric vehicle (EV) percentage: scatter and loess plot



Note: Includes all US census tracts.

Figure E6: Change in tax payments by plug-in hybrid electric vehicle (PHEV) percentage: scatter and loess plot



Note: Includes all US census tracts.

Contact.

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MIT CEEPR

Center for Energy and Environmental Policy Research

MIT Center for Energy and
Environmental Policy Research
Massachusetts Institute of Technology
77 Massachusetts Avenue, E19-411
Cambridge, MA 02139-4307
USA

ceepr.mit.edu

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