Fiscal Progressivity of the U.S. Federal and State Governments*

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Abstract

Combining a variety of survey and administrative data, this paper measures the progressivity of taxes and transfers at the federal level and separately for each U.S. state. The findings are: (i) The federal tax and transfer system is progressive. (ii) State and local tax and transfer systems are close to proportional, on average. (iii) There is substantial heterogeneity in tax levels and tax progressivity across U.S. states. (iv) States that are funded mostly by sales and property taxes tend to have regressive tax systems and low average tax rates. States that are funded mostly by income taxes tend to have progressive tax systems and high average tax rates. (v) State progressivity has remained stable between 2005 and 2016. The unemployment benefit extensions of 2009 temporarily increased progressivity in all states and the state Medicaid expansions since 2014 increased state progressivity differentials. (vi) Considering corporate income and business taxes decreases average state progressivity but increases federal progressivity. (vii) Including state spending on public goods and services as a transfer has a large positive impact on estimated state progressivity.

Keywords: Tax and Transfer Progressivity, State and Local Taxes

JEL Classification: H2, H7, R5

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HOUSEKEEPING SECTION

- **Jon and Kjetil**:
  - Work on explaining and motivating alternative progressivity estimates (PPML and HSVT): para in intro + appendix O. See my proposal you agreed to.
  - state correlates investigation
- **Gianluca**:
  - Work with Jon on state correlates investigation
- **Johannes**:
  - Collapse extensions into one section: keep ext 1, merge 2 and 3, make one table, one tau plot (baseline bars) and one average tax rate plot (baseline bars). Move decomposition etc into appendix. Keep decile plots and make transfers into add/excess medicaid and medicare.
  - Harmonize colors: income taxes: blue; transfers: red; sales taxes: green; excise taxes: brown; property taxes: purple; corporate income tax: teal; business tax: bright red (see fig 25); baseline taxes: gray
  - Review intro and add: we gap the divide between the vast research on poverty and macro tax progressivity by paying meticulous attention to transfer programs and the regional heterogeneity that has been documented and studied by vast literature on anti poverty programs. "Include both enttitlement programs (Medicare) as well as pure transfers, i.e. welfare programs." Fragmented nature of US welfare system. Strong point of our study is that we include comprehensive transfers. Strong point of our analysis: include ALL state taxes and transfers. Hence, our measure includes entire revenue choices of each state government. We aggregate local governments into state level measure.
  - Review section 2 once updated with cons taxes
  - Review intro + literature review. Add: Pechman and Okner (1974) and Triest
  - Update appendix description and review non-JF appendices (cons taxes, spending, alt results)
- **Structure**
  - Baseline: "Direct taxes & Transfers from a cash perspective": All taxes except corpo-

rate income and business. All transfers + 40% Medicaid and 82% Medicare

- Extension 1: "All state taxes & Transfers from a cash perspective": All taxes and all transfers + 40% Medicaid and 82% Medicare
- Extension 2: "All state taxes & Transfers from a cost perspective": Extension 1 + 100% Medicaid, 100% Medicare
- Extension 3: "All state taxes & Transfers from a state budget perspective": Extension 2 + spending on goods/services

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1 Introduction

Rising income inequality in the United States and other countries has rekindled interest in using government redistribution through taxes and transfers as a tool to reduce inequality. A natural first step is to measure the redistribution already taking place through the current tax and transfer system. Most of the U.S. debate has focused on redistribution at the federal level. But tax revenue at the state and local level is large, averaging 8.9% of GDP between 2010 and 2023, compared to 8.0% for federal personal income taxes and 6.4% for federal payroll taxes.[1] Moreover, there is large variation across U.S. states in terms of the level of state and local tax revenue, in terms of the choice of tax base, and in terms of the level and composition of spending. Thus, one might expect substantial differences across states in terms of how much redistribution their tax and transfer systems deliver.

This paper studies taxes and transfers at the state and local levels and contrasts it to progressivity at the federal level. We address three questions. First, how do state and local taxes and transfers impact overall fiscal redistribution? Second, how much variation is there across U.S. states in tax and transfer progressivity? Third, what are the key correlates of this progressivity?

Any attempt to measure redistribution through the tax and transfer system faces a range of measurement choices. We focus on the household as the unit of analysis. Our primary sample is one of working age households, but we also report results for all households. We measure redistribution in terms of current taxes paid and transfers received as a function of current income. We approximate the tax and transfer system using a set of tractable progressivity functions that allows comparisons across time and locations. Moreover, these progressivity functions can be used as budget constraint inputs in heterogeneous agent models. For short, we label the progressivity of the tax and transfer system simply as "tax progressivity."

An important choice is which taxes and transfers to include in the analysis. For our baseline estimates, we focus on taxes and transfers for which we have a high degree of confidence regarding how the amount paid or received varies across households of different income levels. We include all taxes levied directly on households: income taxes, property taxes, and consumption (sales and excise) taxes. For taxes on consumption and property we estimate how the amount of taxes paid varies with current income. On the transfer side we include all the usual transfers plus estimates for the value of Medicaid and Medicare benefits received. Most transfer programs embed a close link between benefit eligibility and current income.[2]

[1] Source: Congressional Budget Office (CBO) and the Census of State and Local Governments (CSLG).

[2] Social security benefits, in contrast, are linked to *lifetime* income, but these are small in our baseline working

Our primary data source is the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS). We supplement this with a range of additional data sets, including the IRS Statistics of Income (SOI), the Consumer Expenditure Survey (CEX), and the American Community Survey (ACS).

Using the ASEC micro data, we calculate state income taxes for each household using the Census Bureau tax model. We impute sales and excise taxes using state-level data on sales tax rates and excise tax revenue, which we combine with estimates of expenditure levels by income based on CEX data. We impute property taxes by matching ASEC households to similar households in the ACS, where property taxes are self-reported. We also model the fraction of property taxes that landlords pass-through to renters. Note that property taxes are typically set at the local level. We also include local income and local sales taxes in our analysis.

The ASEC data report a range of transfers received, which we supplement with CBO imputations designed to address survey under-reporting. We also use administrative data on Medicaid and Medicare spending by state and by household characteristics to estimate the value to enrollees of those programs. We partition transfers into those provided by the federal government and those provided by state and local governments.

One challenge in measuring income and taxes at the top of the household income distribution is that the ASEC income and tax data are top-coded. In addition, realized capital gains are an important source of income at the very top, and these are not reported in ASEC. We therefore use state-level data from the IRS Statistics of Income (SOI) to impute income and taxes to households above a high income threshold.

States also collect considerable revenue from corporate income taxes and from taxes on businesses. In an extension we explore how including these taxes changes the overall tax burden at the state level, and how it changes state-level tax progressivity. This extension requires making assumptions on the incidence of business taxes.

In a second extension we broaden our measure of transfers by including in our transfer measure estimates of the value of state and local government spending on public goods and services.

The key findings from the paper can be summarized as follows. First, the tax and transfer system is progressive at the federal level. Second, state and local tax and transfer systems are close to proportional, on average. Third, there is substantial heterogeneity in tax and transfer progressivity across U.S. states. Fourth, the proximate cause of this variation is the choice of

age sample.

tax base: states relying on sales, excise, and/or property taxes tend to have regressive tax and transfer systems, whereas states relying on income taxes tend to have progressive systems. Fifth, there is a strong positive correlation between state level tax progressivity and the state average net tax rate, where the net tax is defined as taxes minus transfers.

We document large cross-state differences in tax and transfer systems. That finding begs the question of why these differences exist. One important observation here is that tax systems tend to be very sticky, and current state fiscal policy parameters inherit choices made in the distant past. States introduced state income taxes and state sales taxes at different times, with Hawaii, Wisconsin and Mississippi introducing state income taxes before the federal income tax was adopted in 1913. With the exception of Alaska, the states that currently impose neither income nor sales taxes are simply the states that never introduced them. At the same time, however, our estimates of net tax rates and tax progressivity do correlate with various contemporary state characteristics. For example, states with more progressive tax and transfer systems are generally states that recently voted Democrat in Presidential elections; see also Bahl, Martinez-Vazquez, and Wallace (2002), Chernick (2005), Baker, Janas, and Kueng (2020), and Robinson and Tazhitdinova (2023). Does this correlation reflect state-level differences in attitudes toward redistribution? And can those differences can be traced to cross-state differences in demographics or to differences in economic factors, such as measures of income inequality? We leave these questions for future research.

Another set of important questions concerns the implications of differences in tax rates and tax progressivity for inter-state migration and for the distribution of state level economic performance. All else equal, one might expect higher taxes to discourage net migration into a state. But higher net taxes necessarily fund either higher state transfers or higher spending on publicly-provided goods and services. If those are sufficienctly valued, they might outweigh the repelling effects of higher taxes. The implications of tax *progressivity* for migration are more interesting. One might expect a more progressive state tax and transfer system to as an attractor for relatively low income houeholds, but as a repellor for high income households. In a follow-one project, we are using our progressivity estimates to develop and test these implications. Fajgelbaum, Morales, Serrato, and Zidar (2019) and Serrato and Zidar (2016) study how state-level differences in corporate taxation affect investment and the location decisions of firms.

Our paper is related to several strands of literature in public economics. First, we build on a large set of papers aiming to measure the extent of redistribution through taxes and transfers.

Suits (1977) was the first paper to measure tax progressivity for various types of U.S. taxes. He proposes a measure based on Lorenz curves for tax liabilities for various tax bases. He finds that income taxes are progressive while sales taxes are regressive.

Heathcote, Storesletten, and Violante (2017a) and Ferriere, Grübener, Navarro, and Vardishvili (2023) estimate U.S. progressivity at the federal level, incorporating both taxes and transfers. They find that a log-linear relationship between pre-government and post-government income – as proposed by Feldstein (1969), Persson (1983), Benabou (2002) and others – yields a good fit for the federal U.S. tax and transfer system. Guner, Kaygusuz, and Ventura (2014) reach a similar conclusion when focusing strictly on taxes. We compare the ranking of states by tax and transfer progressivity according to this Benabou (2002) / Heathcote, Storesletten, and Violante (2017a) measure with the ranking according to the Suits (1977) index.

Splinter (2020) and Heathcote, Storesletten, and Violante (2020) study how the progressivity of the federal U.S. tax and transfer system has changed over time. Splinter (2020) argues that progressivity, as measured by the Kakwani index, increased over recent decades. Heathcote, Storesletten, and Violante (2020), in contrast, estimate that federal progressivity has not changed much since 1980. Bargain, Dolls, Immervoll, Neumann, Peichl, Pestel, and Siegloch (2015) study how various federal tax policy changes have affected the post-tax distribution of income.

The focus of our paper is on geographical differences in taxes and transfers across U.S. states and the effects these differences have on inequality. The best known evidence on this topic is from the Institute on Taxation and Economic Policy, who put out an annual report called "Who Pays?" (McIntyre, Denk, Francis, Gardner, Gomaa, Hsu, and Sims, 2003). They consider the distributional impact of a similar set of taxes to us, and construct a "Tax Inequality Index". However, their analysis excludes all transfers, and their methodology is largely proprietory. We compare our progressivity ranking to their index.

Sammartino and Francis (2016) find that both federal and state income taxes are generally progressive, but (1) state systems are much less progressive than the federal system and (2) the degree of progressivity varies widely across states. Cooper, Lutz, and Palumbo (2015) measure the effect of income taxes, sales taxes, and some selected excise taxes on state-level redistribution. They find that state-level taxes tend to widen the after-tax distribution of income while federal taxes compress it. Differently from us, they abstract from property taxes and all state-level transfers. Hoynes and Luttmer (2011) use data from the Panel Study of Income Dynamics (PSID) to calculate separately the insurance value and the redistributive value of state-level tax-and transfer programs. They abstract from property taxes and excise taxes.

Gravelle (2007) measures state-level property taxes and documents large heterogeneity in tax burdens across locations and households. Baker, Janas, and Kueng (2020) build a dataset of tax rates at the U.S. county level. Howe and Reeb (1997) provide an historical account on the emergence and evolution of state and local taxes.

Hendren and Sprung-Keyser (2020) estimate recipients' willingness to pay for a large range of transfer programs. They use estimates from Finkelstein and McKnight (2008) to estimate a lower bound for the cash value of Medicare equal to 82% of Medicare spending. Finkelstein, Hendren, and Luttmer (2019) report a similar lower bound for the cash value of Medicaid equal to 40% of spending.[3]

Kosar and Moffitt (2017) and Fleck and Simpson-Bell (2019) study differences in cash transfers and income taxes across states for individuals at the poverty line. In contrast, we incorporate the broadest possible set of taxes and transfers and study state-level differences for the entire distribution of households. Blanchet, Chancel, and Gethin (2022) and Qiu and Russo (2023) compare redistribution through federal taxes and transfers in the United States to that under European tax- and transfers systems.

The remainder of the paper is organized as follows. Section 2 describes our sample and variable definitions and explains in detail how we measure each component of federal and state taxes and transfers. It also introduces our measure of progressivity and provides estimates for federal and state taxes and transfers for the U.S. as a whole. Section 3 illustrates the variation in tax levels and tax progressivity across U.S. states and also shows estimates for the three different sample years we study. In Section **??**, we present extended measures of state tax progressivity which also include corporate income and business taxes. Section 6 concludes. The Appendix contains a comprehensive collection of additional material on our data and methodology.

2 Data and Variable Definitions

Primary data sources Our primary data source is the Annual Social and Economic Supplement (ASEC, "March Supplement") to the Current Population Survey (CPS). Unlike other household surveys, such as the Panel Study of Income Dynamics (PSID) or the Survey of Income and Program Participation (SIPP), the ASEC survey is designed to be representative of

[3]The details of a "no-Medicaid" counter-factual factor importantly into this calculation. If, absent Medicaid, individuals currently Medicaid-eligible would receive more uncompensated care, then part of the value of Medicaid accrues not to recipients but to whoever would otherwise be covering those uncompensated care costs.

the population of each U.S. state, which is central to our analysis. We focus on three two-year periods: 2005-06, 2010-11, and 2015-16.[4]

One limitation of the ASEC survey for measuring income received and taxes paid is that both variables are top-coded. This is a concern, because a small share of high income households account for a large share of total taxes paid. For example, the Internal Revenue Service (IRS) Statistics of Income (SOI) data indicate that in 2016 tax filers with Adjusted Gross Income (AGI) exceeding $500,000 accounted for only 0.87% of all tax returns, but for 35.3% of federal income tax revenues.[5]

To address the top-coding issue, we supplement ASEC data with income and tax data from the IRS-SOI state-level tables. The IRS SOI state-level tabulations report average values for numerous income and tax components for different bins of the adjusted gross income (AGI) distribution.[6] We replace income and tax values for ASEC households with pre-government income exceeding $200,000 in each state with the corresponding values for synthetic households constructed from the SOI state-level tables, drawing from the SOI income bins in proportion to their respective shares of all tax returns.[7]

Income definition Our ASEC measure of gross pre-government income is similar to that of Heathcote, Storesletten, and Violante (2017a). It includes pre-tax income from wages and salaries, business and professional practice, farming and cropping, interests and dividends, rents and royalties, as well as assistance from friends and relatives (private transfers). Our income measure for our synthetic SOI households is total income (IRS form 1040 line 9) minus unemployment compensation minus taxable social security income.[8] Realized capital gains are not available in the ASEC, but they are included in measured income for our synthetic high income SOI households.[9] For households with wage income we add the employer-paid portion of payroll taxes (which is identical to the employee-paid value) to our pre-government income measure.

add citations Note that the reported income in ASEC and the SOI falls short of aggregate per-

[4]We pool observations over adjacent years to increase sample size. Figure 33 in Appendix C.1 shows that, for all of our sample years, we have no fewer than 500 households in each state in our sample.

[5]IRS SOI Table 2. "Individual Income and Tax Data, by State and Size od Adjusted Gross Income, Tax Year 2016."

[6]The top three bins for 2010, 2011, 2015 and 2016 are $200,000 to $500,000, $500,000 to $1m, and $1m plus. In 2005 and 2006 the top bin is $200,000 plus.

[7]We retain the ASEC measures for government transfers and the household-level ASEC weights.

[8] Note that our SOI income measure misses non-taxable components of income, such as tax-exempt interest income.

[9]According to the IRS, in 2016, 86% of total realized capital gains accrued to households with AGI above $200,000, which is the threshold above which we replace ASEC income and tax variables with their synthetic SOI counterparts.

sonal income as measured in the National Income and Product Accounts. This shortfall is most pronounced for business income (see, for example, Rothbaum, 2015, and Imboden, Voorheis and Weber, 2023). We estimate *actual* net taxes paid across the *reported* income distribution. If reported income is less than true income, our reported tax rates will be too high. Furthermore, if under-reporting of income were especially severe at relatively high income levels, but our estimates for net taxes paid given reported income are correct, then our reported tax rates for the rich, and thus our estimates for tax progressivity, will be too high. One possible remedy for this problem would be to pose a model for missing income and to use it to inflate the income values reported in the ASEC and SOI data so as to match "true" income. Piketty, Saez and Zucman (2018) and Auten and Splinter (2024) both attempt such an exercise, but make different assumptions on how unreported income is distributed. Researchers interested in using our estimates can decide whether and how to inflate the reported income distribution before translating our estimates for net taxes paid into effective net tax rates.

We define post-government income to be pre-government income minus taxes plus government transfers.

Taxes For each household in our sample we will measure or impute estimates for a range of federal and state and local taxes.

Federal taxes comprise federal income taxes, federal payroll (FICA) taxes (both the employer and employee portions and the self-employment payroll tax) and federal excise taxes. In an extension we include federal corporate taxes.

State and local level taxes comprise state and local income taxes, property taxes, sales taxes, and state and local excise taxes and user charges.[10] In an extension we include state-level corporate taxes, business property taxes, and sales and excise taxes which apply to business purchases of goods and services.

Note that the SOI data which we incorporate for high income households have several useful features for estimating taxes. First, the SOI tables report actual federal income taxes paid. Second, the vast majority of high income households itemize deductions in their tax returns, and the SOI data report deductions for state income taxes and for property taxes paid.[11] We use that information to impute state income taxes and property taxes to our synthetic SOI households. Appendix B.3 reports effective tax rates by state for SOI households with Adjusted

[10]"Local" taxes include all taxes set at the sub-state level, including County, Municipality, Township, Special District and School District taxes.

[11]For example, 93.7% of households with AGI exceeding $200,000 itemized in 2016.

Gross Income between \$500,000 and \$1m in 2016.

Transfers As with taxes, transfers can be partitioned between those that are set at the federal level versus those that are set by state or local governments.

Federal transfers that are included in our baseline transfer measure are Social Security Disability and Survivor Benefits, Supplemental Nutrition Assistance Program (SNAP) income, veterans benefits, Supplementary Security Income (SSI), survivor's benefits, school lunch benefits, disability benefits, and housing assistance. We include Social Security Old-Age Benefits, although these are quite small for our sample of working age households. We also include Medicare, where we measure the value of the benefit for eligible households at 82% of state-specific spending per enrollee, following Hendren and Sprung-Keyser (2020).

State and local transfers are Unemployment Insurance (UI) payments, workers' compensation, and, for households living in Alaska, Alaska Permanent Fund Dividend (APFD) receipts.

Two transfer programs have both federal and state components, which we split between both levels of government. One is Medicaid. Medicaid is a very large program, and the choice of how to whether and how to include it is important when measuring redistribution. Our model, following Finkelstein, Hendren, and Luttmer (2019), assumes that the value of Medicaid to recipients is equal to 40 percent of administrative per enrollee Medicaid spending. The other joint federal-state program is Temporary Assistance for Needy Families (TANF).

In addition to our baseline model of transfers, we will also report results for a broader measure. In this broader measure we value Medicare and Medicaid spending at 100% of their corresponding expenditure levels. In addition, our broad transfer measure includes estimates of state per capita spending on public education and on other goods and services.

Sample The unit of observation is the household. In our baseline calculations, we follow the same sample construction criteria as Heathcote, Perri, and Violante (2010) by selecting households with heads aged between 25 and 60 with a minimal labor force attachment. Specifically, we retain households where at least one spouse has at least an earned income equivalent to working part-time at the federal minimum wage (\$7,250 in 2016). This attachment requirement implies that we drop 4.1% of households in that age range. In our robustness analysis we relax the age and income restrictions, and include all households. Appendix C shows that, once ASEC weights are used, the state-level population shares in our sample line up closely with the official Census counts.

	Federal Taxes and Transfers			State & Local Taxes and Transfers		
		Sample	All		Sample	All
Taxes	Income	15.15	15.48	Income	3.89	3.89
	FICA (employee+employer)	10.39	10.31	Property	2.27	2.89
	Excise	0.37	0.46	Sales	1.54	1.76
				Excise	0.81	1.00
	Corporate Income	2.80	3.09	Corporate Income	0.48	0.54
				Business	2.84	2.92
Transfers	Medicaid* (cash value)	0.61	1.03	Medicaid* (cash value)	0.47	0.78
	Medicare (cash value)	0.56	4.77	Unemployment Benefits	0.16	0.19
	Social Security Disability and Survivors Benefits	0.40	0.95	Worker's Compensation Benefits	0.07	0.11
	Social Security Old Age Benefits	0.35	6.39	TANF*	0.01	0.03
	SNAP	0.34	0.65	Alaska Permanent Fund Dividend	0.01	0.01
	Veteran's Benefits	0.22	0.56			
	Disability Benefits	0.18	0.35			
	SSI	0.17	0.53			
	Survivor's Benefits	0.16	0.49			
	School Lunch	0.11	0.12			
	Housing Assistance	0.09	0.36			
	TANF*	0.01	0.03			
	Public Spending	3.12	4.40	Public Spending	7.45	8.30

Table 1: Classification of federal and state and local taxes and transfers. The first column of numbers is for our sample of ASEC households (working age and income at or above working part-time at the federal minimum wage). The second column is for all households included in the ASEC dataset. Taxes and transfers are reported as shares of pre-government household income. Pre-government income is $81,607 for all households in the ASEC dataset and $119,534 for households in our sample. Transfers marked with an asterisk have both federal and state components. The data shown refer to sample years 2015/2016 and have been computed using ASEC household weights.

Table 1 summarizes the federal versus state and local components of taxes and transfers, and reports the average values for those taxes and transfers relative to average pre-government household income in 2015-16. Note that Social Security and Medicare are much less important for households in our working-age sample than they are for the entire set of U.S. households.

We now provide more detail on how we measure all the different components of taxes and transfers described above.

2.1 Income Taxes, including FICA Taxes

The ASEC dataset contains estimates of federal and state income taxes calculated through the Census Bureau tax imputation model. While this model is similar to the National Bureau of Economic Research (NBER) TAXSIM model, it also integrates confidential IRS and ASEC data to deliver more accurate measures of some income components (such as capital gains) as well as tax credits (such as the Earned Income Tax Credit (EITC) and Child Tax Credit), deductions, and exemptions.[12]

On top of federal and state income taxes, some counties, cities and school districts impose additional income taxes. These local taxes are generally proportional to income. The SOI's state income tax measure includes local taxes paid and the Census Bureau's tax model includes them in some states (Indiana, Maryland and New York) in select years. For the states and years in which they are not included, we measure local income tax revenue by state from the Census of State and Local Governments, and allocate this proportionately to income across all state residents.[13]

Federal payroll taxes (Federal Insurance Contributions Act, FICA) are the sum of Social Security ("Old-Age, Survivors, and Disability Insurance", OASDI) and Medicare ("Hospital Insurance", HI) taxes. The corresponding tax rates are 6.2% and 1.45%, respectively, for both the employer and the employee, resulting in a total rate of 15.3%. These taxes apply to wage income. Importantly, the Social Security tax only applies to income up to the OASDI limit ($118,500 in 2016) while the Medicare tax base is uncapped. A similar tax, with the same 15.3% total rate, applies to income from self-employment.

The Census Bureau tax model provides estimates for the employee portion of the FICA taxes paid, while it reports the total self-employment FICA tax. We therefore add estimates for the employer-paid portion of FICA taxes paid for wage and salary income to the ASEC FICA variable. We also add this same amount to our household pre-government income variable.

The IRS-SOI total tax liability variable includes FICA taxes for the self-employed. However, the SOI tax tables, which are based on 1040 tax forms, include neither the employer nor the employee portions of FICA taxes on wage and salary income. We therefore use the SOI wage and salary income variable to estimate and impute FICA taxes (employer plus employee portions)

[12]See O'Hara (2006), Webster (2011), Lin (2022), and Wheaton and Stevens (2016) for a description of this model and for a comparison with other tax imputation models such as TAXSIM.

[13]The public version of the ASEC survey does not provide sufficiently granular household location information to impute local taxes at the county, city or school district level. See Appendix D for more details on local income taxes and our imputation procedure.

that apply to wage and salary income. We also add the employer portion to household income.

Figure 1 plots income and payroll taxes paid, as a share of pre-government income, for different deciles of the household income distribution. In aggregate, income and payroll taxes collect around 30 percent of household income. Both federal and state income taxes are strongly progressive. In particular, thanks to the EITC and other tax credits, low income households effectively pay negative federal income taxes. However, the progressivity of income taxes is somewhat offset by the fact that FICA taxes are capped, and thus the effective FICA tax declines at the top of the income distribution.

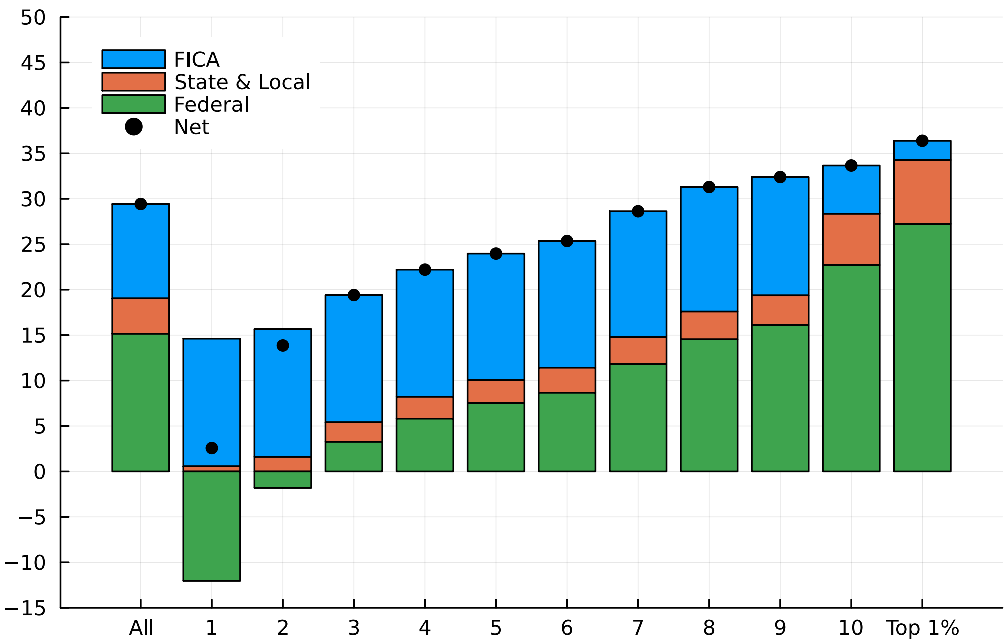

Figure 1: Average income tax rates (Federal, State & Local) and FICA tax rates for 2015/2016. Rates are plotted for all households, for 10 deciles of the household pre-government income distribution, and for the top 1% of households by income. For each bin, tax rates are computed as average taxes paid divided by average within-bin pre-government income. The tax and income values are reported in Table 3.

2.2 Sales and Excise Taxes

Households pay taxes on their consumption expenditure via sales and excise taxes. These occur mainly at the state and local level. The federal government levies excise taxes on a small set of goods, including gasoline, alcohol, and tobacco.[14] Our strategy for imputing household-level sales and excise taxes is to multiply good-specific sales and excise tax rates for each good by household-level consumption expenditure on that good. This procedure requires two basic

[14]We ignore federal government taxes on imported goods via tariffs.

inputs – imputed consumption levels and estimated average tax rates.

Consumption functions: We start by estimating household consumption expenditures on different categories of goods and services as a function of household income. The Consumer Expenditure Survey (CEX Table 1203) reports average household expenditure for different quantiles of the income distribution for different types of spending. This data is for the U.S. as a whole. We impute consumption functions by linearly interpolating between the CEX bin-mean income values. For income levels outside this range (i.e., below the lowest income level and above the highest income level), we use a log-linear extrapolation. For every good j we scale the consumption function so that, when aggregated across all households in our ASEC/SOI sample, aggregate imputed expenditure on good j equals aggregate expenditure on this good as reported by the BEA in the National Income Accounts. The motivation for this adjustment is that some components of spending are under-reported in the CEX while others are over-reported (see Garner, Janini, Paszkiewicz, and Vendemia, 2006).[15] Expenditure in the CEX survey is inclusive of sales and excise taxes. We therefore impute state-level pre-tax consumption expenditure by dividing by state-specific gross tax rates, the calculation of which we describe below.

Sales tax rates on goods: The Tax Foundation reports, for every year, standard state sales tax rates and average within-state local sales tax rates. We apply these rates to most categories of goods, except for food consumed at home, drugs, and goods subject to excise taxes. Prescription and non-prescription drugs are almost universally tax-exempt, so we treat all healthcare spending as exempt from sales taxes. Food consumed at home is often untaxed or taxed at a reduced rate; we use the food-at-home tax rates reported in the Book of the States. We assume food consumed away from home is taxed at the standard state and local tax rate.

Sales taxes on services: There is considerable cross-state variation in the sales tax treatment of services. Some are tax exempt, some are taxed at the standard rate, and some are taxed at special rates. We base our estimates for the tax rates on services on a 2007 survey by the Federation of Tax Administrators, which reports state-specific tax rates for 168 services, which we match to different components of spending in the Consumer Expenditure Survey (CEX). We project these service tax rates to other years by assuming that service tax rates are fixed proportions of the standard state sales tax rate.

Tax rates on excise-taxable goods: We measure excise taxes for the following six components of expenditure: tobacco, alcohol, motor fuels, public utilities, amusements, and insurance. We

[15] Appendix E details the adjustment factors for each good.

label these "excise-taxable goods".

Motor fuels, alcohol and tobacco are subject to federal excise taxes. We estimate average tax rates by dividing federal tax revenue by aggregate pre-tax expenditure on those goods (source: BEA).[16]

For taxes at the state and local level, we estimate excise tax rates by dividing reported state selective sales and gross receipts tax revenue for these goods by aggregate imputed state-level pre-tax consumption expenditure on the same goods. Estimates of revenue from taxes on these goods at the state level are reported in the Census of State and Local Governments (CSLG) and the Book of the States. Our interpretation is that these revenue estimates include both excise taxes and sales taxes applied to these goods. Thus, we will henceforth use the label "excise taxes" as shorthand for all taxes tied to consumption of excise-taxable goods. For tobacco, alcohol, motor fuels, and public utilities we obtain tax revenue at the state and local level from the CSLG. For amusements and insurance we obtain state level tax revenue from the Book of States.

We assume that households pay all tax revenue on tobacco, alcohol, amusements, and insurance. Following Minnesota Department of Revenue: Tax Research Division (2024) we assume that 2/3 of taxes on motor fuels are paid by households and 1/3 by businesses. We assume the same split for taxes on public utilities.

Taxes paid: Finally, to estimate taxes paid for a household with income y, we multiply tax rates by pre-tax imputed consumption, and sum across spending categories.[17]

Figure 2 plots our estimates of sales and excise taxes paid for different deciles of the household pre-government income distribution. These taxes are clearly regressive, with low income households facing much higher effective rates than richer ones. Consumption taxes – expressed as a share of pre-tax income – for households in the bottom eight deciles are higher than the average rate of 3.3 percent.

[16] Note that BEA consumption is reported inclusive of sales and excise taxes, so effective tax rates are given by tax revenue divided by expenditure minus revenue.

[17] Note that, because we use measures of revenue to estimate effective tax rates on excise-taxable goods, our approach replicates excise tax revenue at the state level. In contrast, we use statutory rates for non-excise-taxable goods and services, and apply them to spending estimated at the U.S. level. Appendix Figure **??** shows that our model replicates aggregate sales tax revenue quite well at the state level.

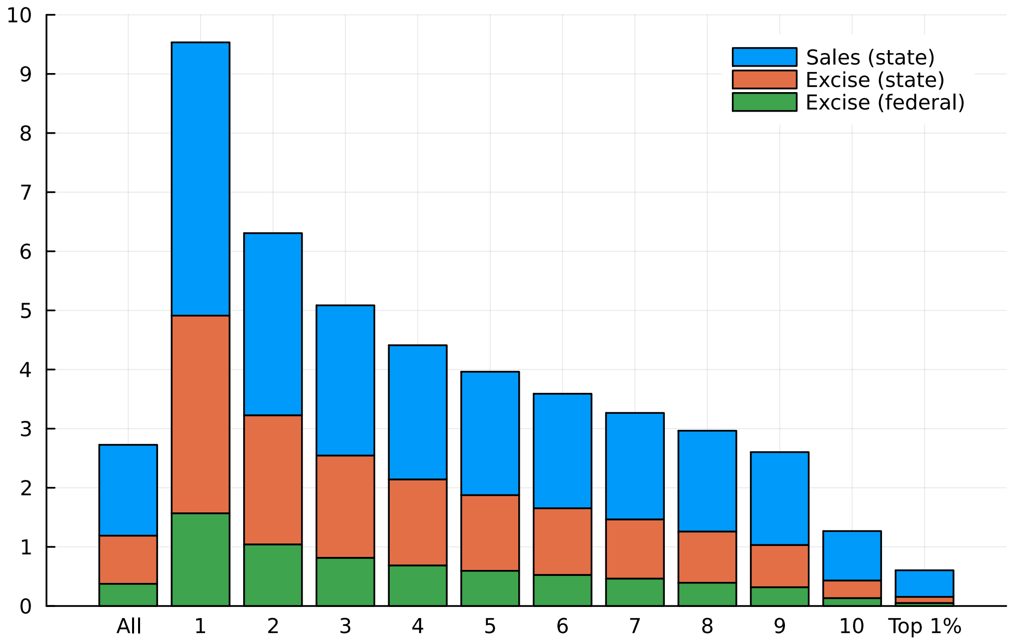

Figure 2: Average consumption taxes expressed as a share of pre-tax income for 2015/2016. See notes to Figure 1.

There are two reasons why sales and excise taxes are regressive. The first, and most important reason, is that consumer spending rises less than proportionately with income. The second reason is that lower income households consume different and more heavily taxed consumption bundles than richer households.

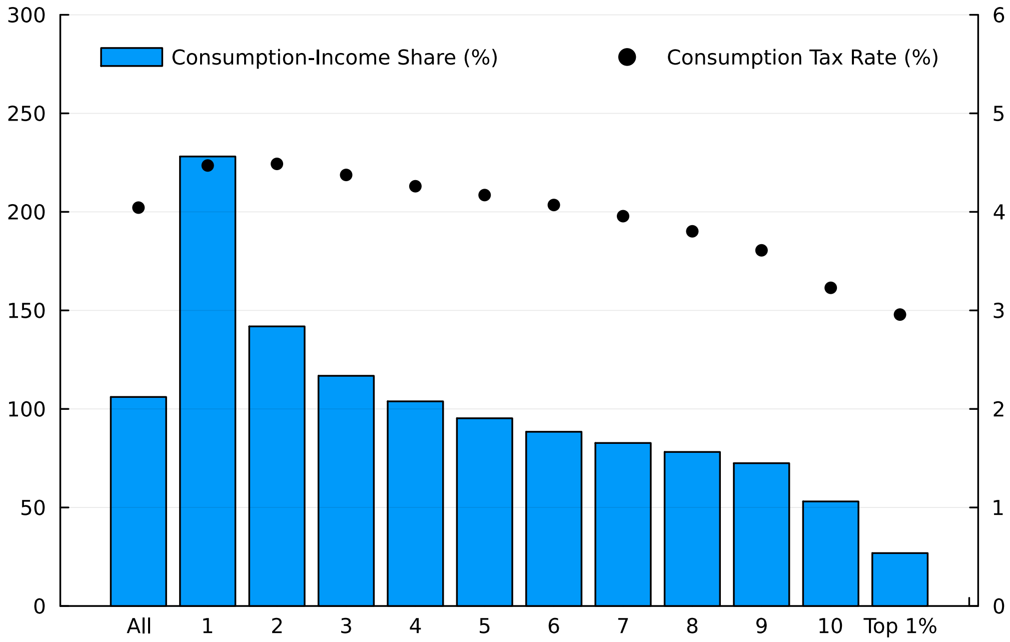

Figure 3: The figure plots spending shares and consumption tax rates by income for 2015/2016. Average consumption spending-income shares (bars, left axis) are computed as household pre-tax consumption spending divided by pre-government income. Average consumption tax rates (dots, right axis) are computed as household consumption taxes paid divided by pre-tax consumption spending. See notes to Figure 1.

Figure 3 illustrates both of these sources of regressivity. It shows total household consumption spending as a share of pre-government income (blue bars, left axis) and the effective consumption tax rate (black dots, right axis) for different groups of the household pre-government income distribution. Note that the consumption tax rate in this figure is consumption taxes as a share of pre-tax consumption expenditure. Spending rates decline rapidly with pre-government income, which is the mirror image of the well known fact that higher income households have higher savings rates. Consumption tax rates decline with income because higher income households tend to consume more goods relative to services, and services are generally more lightly taxed. In addition, utilities, fuel, alcohol and tobacco are especially heavily taxed, and the shares of income devoted to these items decline very sharply with income.

Figure 3 shows that our measure of consumer spending exceeds pre-government income for a large share of the population. There are two reasons for this. First, the plot shows spending as a share of income before taxes and transfers. The lowest income deciles receive significant transfer income (see Section 2.5), implying a much lower consumption rate out of income inclusive of transfers and taxes. Second, recall that we have rescaled the various components of consumption to match corresponding aggregate estimates in the National Income accounts.

But we have not similarly rescaled household income: all the tax rates we report are relative to pre-government income as reported in our merged ASEC / SOI sample. As discussed in Section 2, income is likely under-reported.[18]

2.3 Property Taxes

Homeowners typically pay property taxes to local governments. Renters are not directly liable for property taxes, but we will assume that landlords pass on, in the form of higher rents, a portion of the property taxes levied on rental property.

Homeowners For households whose income is above the threshold for replacement, we estimate property taxes using the IRS-SOI 'real estate taxes' variable. For other households (the vast majority), we impute property taxes to homeowners using a matching procedure which maps households in our ASEC sample to observationally similar households in the American Community Survey (ACS). The ACS contains self-reported data on house values, rents, and property taxes.[19] We match each ASEC household with the household's 9 nearest neighbors in the ACS, and impute to the ASEC household the average property taxes paid by those 9 ACS households. For this matching procedure, we insist that the matched ACS households are homeowners, and that they reside in the same state as the ASEC household (and the same county where county is reported). Within that pool, we search for ACS households that are as similar as possible in terms of household income, household head's education, and the number of housing units in the structure in which they live.

The ACS property tax data have one limitation, which is that the property tax variable is top-coded at a relatively low and year invariant level: $10,000. This presents a problem for states with high property taxes. For example, property taxes are top-coded for 35 percent of homeowners in New Jersey in 2015/16. Fortunately, top-coding is much less restrictive for home values. We therefore impute property taxes to property-tax top-coded households by multiplying state- and year-specific property tax rates by self-reported home value. We estimate those tax rates at the state level using all the ACS homeowners for whom neither property taxes nor home values are top-coded.

[18]The implied aggregate components of personal income in our ASEC/SOI dataset can be calculated from Appendix Table 7. ASEC accounts for 98% of salary and wage income in the National Accounts but only about 60% of aggregate personal income over and above worker compensation.

[19]In contrast, the raw ASEC data has only an imputed value for property taxes. In addition, the Census Bureau imputation procedure was changed substantially in 2011 and no longer uses detailed location information for later years, which is critical for assessing variation in tax rates across states. We thank Daniel Lin for providing this information.

Renters There is ample evidence that property taxes nominally paid by landlords are passed through to tenants (e.g. Tsoodle and Turner, 2008; Baker, 2024). In ASEC data we can identify renters, but we do not observe rent paid, nor what portion of this rent constitutes pass-through of property taxes. We therefore follow a multi-step procedure to impute estimates of property taxes that are passed on to ASEC renters.

First, we match ASEC renters to renters in the ACS following a similar 'k nearest-neighbors' matching procedure to the one described above for owners. This step gives us county and year-specific estimates for rents paid at the household level. Second, we translate rents into estimates for home values using county-specific price-to-rent ratios from Zillow. Third, we multiply these home value estimates by county and year-specific property tax rates (see the previous section) to estimate the tax bill due on the rental unit. Finally, we apply a structural model of pass-through to estimate the share of this tax bill that is passed on to the tenant in the form of higher rents and consider this amount as the property tax paid by the renter.

Our pass-through model is described in detail in Appendix F.1. The model relies on the idea that in regions where home value primarily reflects inelastically-supplied land, property taxes will be born by landlords. In contrast, where home values primarily reflect the value of elastically-supplied structures, the long-run incidence of property taxes will fall on renters. In particular, higher local property taxes will depress new construction and boost rents to the point where landlords can earn a common economy-wide after-tax return.

Let $\gamma_{c,t}$ denote the share of property taxes passed-through to renters in county c in year t. In our simple model,

$$\gamma_{c,t} = \frac{1 - \lambda_{c,t}}{1 - \lambda_{c,t} t^{p}_{c,t} \left(\frac{P}{R}\right)_{c,t}} \tag{1}$$

where $\lambda_{c,t}$ is land's share of home value in county c in year t, $t^{p}_{c,t}$ is the property tax rate, and $\left(\frac{P}{R}\right)_{c,t}$ is the price-rent ratio. Note that as $\lambda_{c,t} \to 1$, $\gamma_{c,t} \to 0$, while as $\lambda_{c,t} \to 0$, $\gamma_{c,t} \to 1$. To implement this model, we use estimates of land's share of home value from Davis, Larson, Oliner, and Shui (2021) along with our own county-level estimates for property tax rates and the Zillow county-level price to rent ratios.[20]

Figure 4 plots the distribution of our property tax pass-through estimates. Pass-through coefficients range between 60 and 85 percent for most counties, with lower pass-through in high land value states including California, Hawaii, Massachusetts, and Rhode Island.

[20]For some counties, county identifiers are missing in the ACS for at least one of the variables that enter our pass-through formula. Because of this limitation, pass-through coefficients can only be estimated at the state level

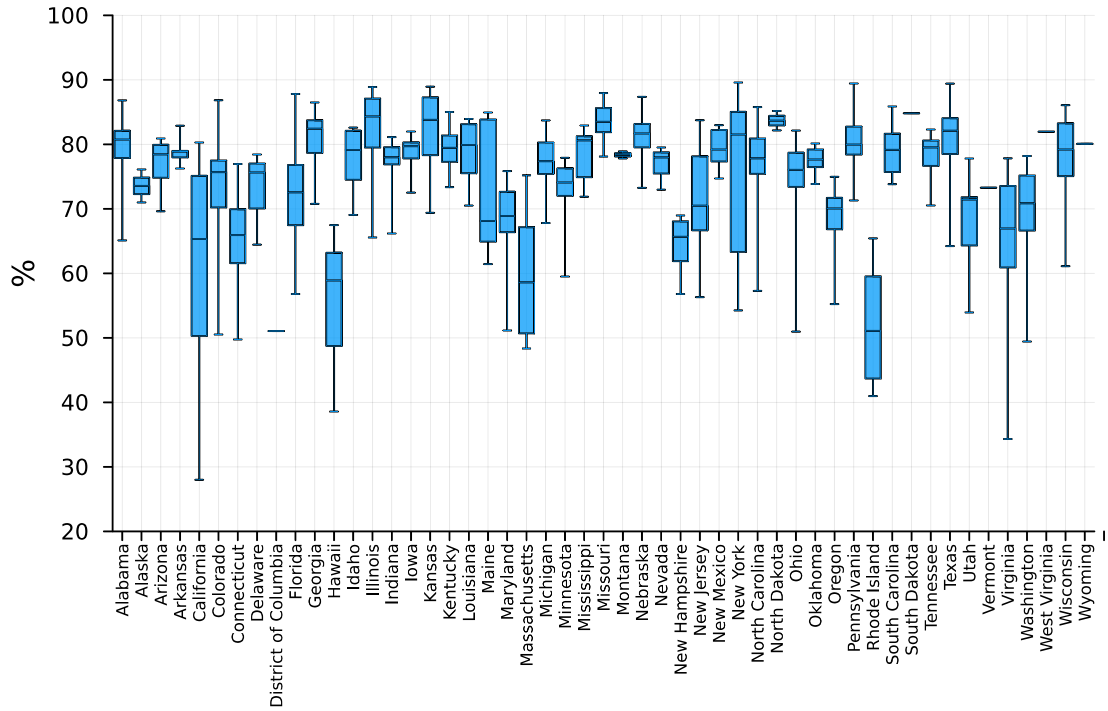

Figure 4: Pass-through by county 2015/2016. For each state, the outer ticks show the within-state range of estimated pass-through coefficients across counties. The shaded area plots the inter-quartile range across counties, while the tick in the middle represents the median county.

Appendix F provides additional details on all aspects of our property tax imputations.

To illustrate the property taxes imputed into our sample in this way, Figure 5 plots property taxes paid (directly or indirectly in the form of higher rents) as a fraction of pre-government income for households in different deciles of the income distribution. It is clear that property taxes are regressive, with effective tax rates declining strongly with income. While property taxes claim at least two percent of income for the poorest 90 percent of households, they account for only one percent of income for the richest one percent. Property taxes are regressive even though imperfect pass-through means that renters – who are disproportionately lower income – tend to pay lower property taxes than homeowners (see Table 3).[21]

To understand the source of property tax regressivity, consider Figure 6. It plots the relationship between mean home values (for homeowners) and rents (for renters) for different pre-government income vingtiles in the American Community Survey. If housing consumption was proportional to income, one would expect a linear relationship of home values and rents to income, with a slope equal to unity, reflecting homothetic spending behavior. The figure

for a few small states, for example Wyoming.

[21]Table 6 in the appendix also reports the share of home-owners by income group.

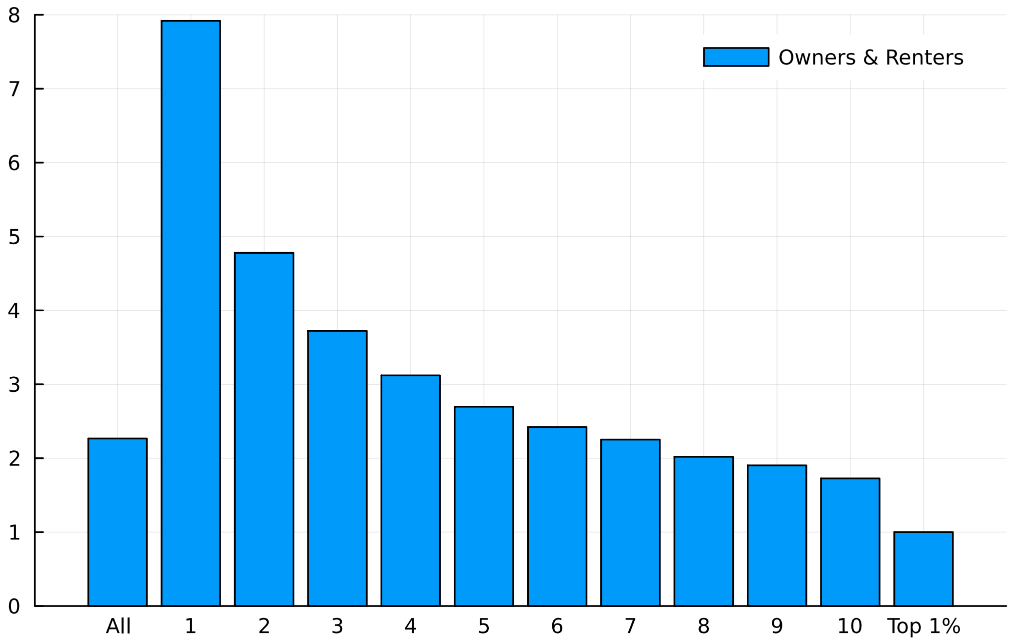

Figure 5: Average property tax rates 2015/2015. See notes to Figure 1.

indicates a different empirical relationship. Home values increase less than proportionally to income, especially at low income levels where home values are almost flat at around $180,000 up to annual incomes of around $45,000. Rents also increase less than proportionately with income. As property taxes are typically proportional to home values, and home values tend to be proportional to rents, these patterns help explain why property taxes are regressive, particularly at low income values.

2.4 Comparing Imputed Taxes to External Estimates

review One important test of our imputation models for income taxes, sales and excise taxes and property taxes is to compare our estimates for total taxes paid, aggregated across households in our ASEC / SOI sample, to external estimates of the revenue collected from those taxes. The Census Survey of State and Local Government Finances provides such estimates at the state level. In Appendix G we compare the total revenue we impute to each of these taxes to the revenue numbers reported there. We find that our model for income taxes matches the Census data on state income tax revenue very closely. Our model for property taxes also performs well. Our model for sales tax revenue aligns less closely, while our excise tax revenue estimates perfectly replicate (by construction) the Census numbers.

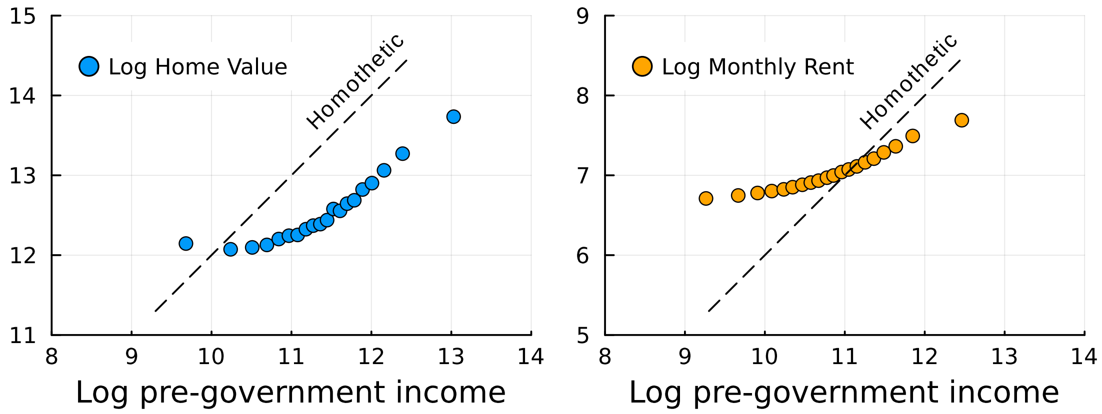

Figure 6: Home values (for owners) and rents (for renters) by pre-government income. Each dot represents the average within one vingtile of households, where households are ranked according to pre-government income. Source: ACS (2015/2016).

2.5 Transfers

Table 2 summarizes the transfers we include, how we categorize them as federal versus state and local, and the source we use to measure them. Note that we retain the ASEC transfer measures for high income households, even though we replace their income and tax values using IRS-SOI-based estimates.

Federal Transfers: The largest federal transfer program is Social Security, which is self-reported in ASEC. Note, however, that Social Security income is relatively small for our baseline working-age sample of households, because few members of these households are claiming Old-Age benefits.[22] Social Security also has Survivors' Income and Disability Insurance components. These components are not reported separately in ASEC, which contains a single Social Security income variable. We therefore use age to split out the Old-Age component of Social Security: if a Social Security recipient is below age 62, we assume their eligibility is through Survivor or Disability Insurance components of the program. Otherwise, we assume eligibility is attributable to Old-Age.[23]

Medicare is another very large program. The IPUMS ASEC data include a flag to indicate whether individuals are covered by Medicare. We follow Habib (2018) at the Congressional Budget Office who augments the ASEC survey information with an imputation model to address under-reporting. In terms of the value of benefits received to those individuals who

[22]In this paper we measure actual Social Security Old Age benefits received as part of current transfers. That approach is consistent with our goal of measuring current taxes and transfers as a function of current income. In Heathcote, Storesletten, and Violante (2017a) we took a different approach, imputing to each household an estimate of the annualized discounted present value of future expected Social Security benefits.

[23]We thank Amanda Michaud for this suggestion.

Transfer Program	Federal	State	Source
School Lunch	x		ASEC, self-reported (SCHLLUNCH)
Veterans Benefits	x		ASEC, self-reported (INCVET)
Survivors Benefits	x		ASEC, self-reported (INCSURV)
Disability Benefits	x		ASEC, self-reported (INCDISAB)
Social Security Survivor and Disability Benefits	x		ASEC, self-reported (INCSS, recipient age < 62)
Social Security Old-Age Benefits	x		ASEC, self-reported (INCSS, recipient age ≥ 62)
Supplemental Nutrition Assistance Program	x		ASEC (CBO imputed); see H.1 for details
Supplemental Security Income	x		ASEC (CBO imputed)
Housing Assistance	x		ASEC (CBO imputed); see H.3 for details
Medicare	x		Imputed as described in H.6
Unemployment Insurance		x	ASEC, self-reported (INCUNEMP)
Workers Compensation		x	ASEC, self-reported (INCWKCOM)
Alaska Permanent Fund Dividend		x	Imputed using ASEC variables as described in H.4.
Temporary Assistance for Needy Families	x	x	ASEC (INCWELFR); split as described in H.2
Medicaid	x	x	Imputed and split as described in H.5

Table 2: Assignment of each transfer component to federal and state budgets. For ASEC variables, the source column provides the IPUMS variable name.

are imputed benefits, we rely on the Centers for Medicare and Medicaid Services, who report Medicare-financed health expenditure per enrollee by state. They also report Medicare spending per enrollee for different age groups at the national level; we assume the same age distribution applies in all states. However, the dollar value to recipients of Medicare spending may be lower than the amount spent (this is an issue for all in-kind transfers). We adopt a conservative assumption for that dollar value, assuming it is equal to the amount by which Medicare eligibility reduces out of pocket health expenditure and spending on private insurance, which is 82% of Medicare expenditure according to Hendren and Sprung-Keyser (2020) and Finkelstein and McKnight (2008).

We also adopt the CBO imputation model for other components of federal transfers that are known to be under-reported in the ASEC survey.[24] The transfers the CBO model imputes are the Supplemental Nutrition Assistance Program (SNAP) which provides food stamps, Supplemental Security Income, and federal housing assistance. For these transfers we adopt the CBO-adjusted version of ASEC transfers.[25] The CBO model also imputes Medicaid transfers, which we discuss below.

Other federal transfer programs we include are School Lunches, Veterans' Benefits, Survivors' Benefits, and Disability Benefits. We take values for these transfers straight from the ASEC data.

[24] See Habib (2018) and `https://github.com/US-CBO/means_tested_transfer_imputations` for details.

[25] There are some state-level housing subsidies but we abstract from them as they are very small in comparison to federal subsidies. See H.3 for details.

State transfers: There are three transfer programs that we classify as operating at the state level: Unemployment Insurance, Worker's Compensation, and, for Alaska, dividends from the Alaska Permanent Fund (APFD). We rely on ASEC self-reported values for the first two of these. APFD are not straightforward to measure in ASEC and we therefore develop an imputation strategy using information provided by Berman and Reamey (2016).

Joint federal-state transfers: Two transfer programs, Medicaid and Temporary Aid to Needy Families (TANF), are funded by both the federal government and by state governments. For both these programs, states have latitude to set eligibility criteria and benefit generosity. We split these transfers into federal and state components in proportion to their respective state-specific federal versus state spending splits. For TANF we rely on the self-reported value of transfers in ASEC. The amount of TANF funding each state receives from the federal government is based on the level of state spending prior to 1996 on the earlier Aid to Families with Dependent Children (AFDC) program.

Medicaid is the largest of all means-tested transfer programs but Medicaid receipt is severely under-reported in the ASEC survey. The CBO's imputation model is designed to replicate administrative targets for Medicaid receipt and spending per enrollee across different Medicaid enrollment groups: adults, children, disabled individuals, and seniors. However, the CBO model is not designed to match these targets at the state level. We therefore adapt and extend their imputation model to replicate enrollment and spending targets state-by-state. Figure 7 illustrates wide cross state variation in Medicaid spending per household.

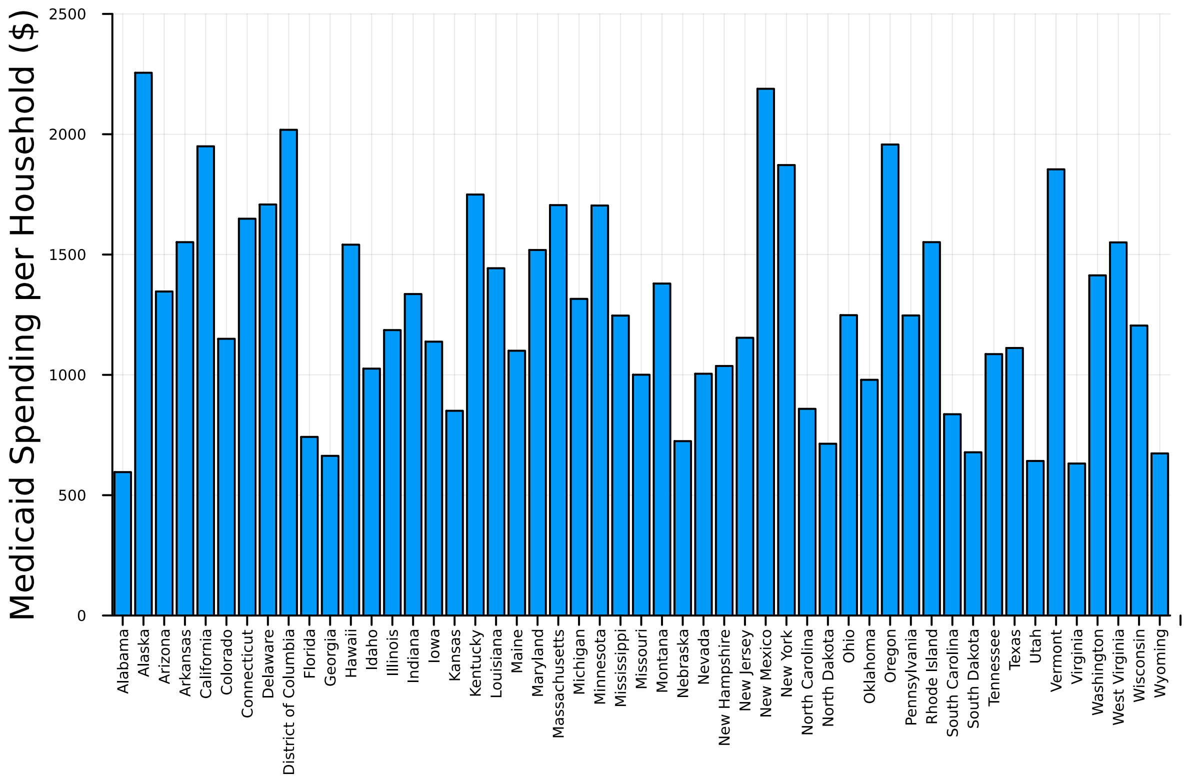

Figure 7: Medicaid spending per household in our baseline sample (2015/2016). These are unconditional averages. Cross-state variation reflects a mix of variation in enrollment rates plus variation in spending per enrollee.

Finally, we translate dollars spent on Medicaid per enrollee to an equivalent cash value per recipient by assuming that the latter is equal to 40 percent of administrative per capita Medicaid spending, following Finkelstein, Hendren, and Luttmer (2019). This amounts to the average increase in medical spending due to Medicaid plus the average decrease in out-of-pocket spending due to Medicaid. State-level spending on Medicaid is matched by federal dollars, using state-specific Federal Medical Assistance Percentage (FMAP) matching rates that are based on state-level per capita income. We use those FMAP rates to apportion our Medicaid transfer values into federal versus state components.

Appendix H contains a more exhaustive description of all aspects of transfer measurement.

Figure 8 plots transfer rates by income. Transfers are generally very progressive, as expected. Total transfers exceed 65 percent of pre-government income for households in the bottom decile of the pre-government income distribution, while they are negligible for households at the top.

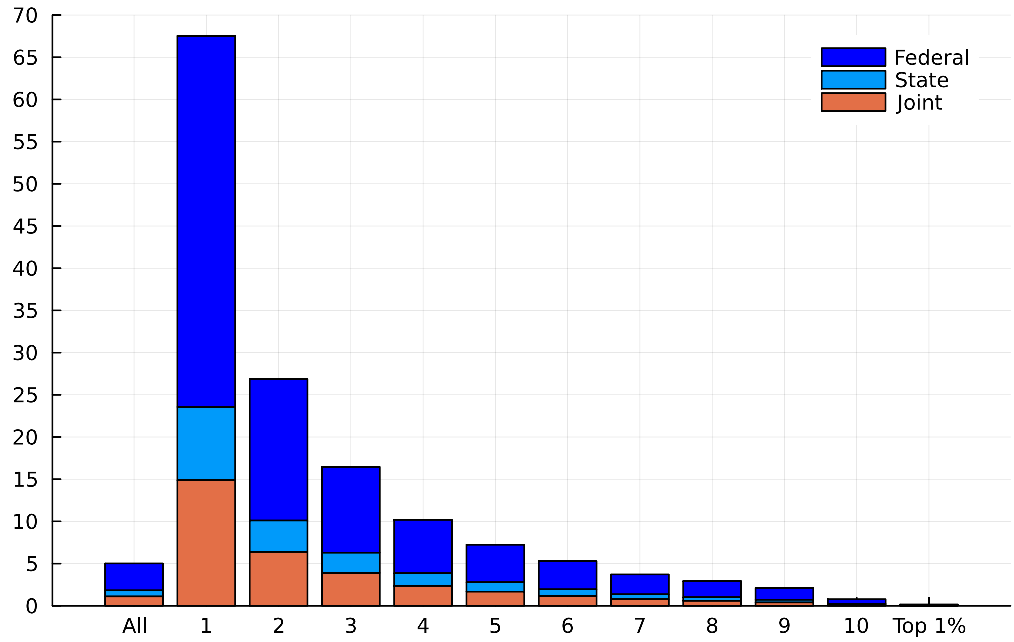

Figure 8: Average transfer rates 2015/2016. See notes to Figure 1.

2.6 All Taxes Net of Transfers

Figure 9 plots average net tax rates: the sum of all the taxes discussed above, minus the transfers plotted in Figure 8.

Table 3 reports income, tax and transfer values by income decile for all the taxes and transfers discussed above. This table is for our baseline working age sample, pooling years 2015 and 2016. Table 6 in Appendix C.2 is a more comprehensive version of this table. Table 7 in Appendix C.2 reports the same statistics for the entire ASEC dataset (i.e., before dropping households that do not satisfy our age- and income-based sample selection criteria).

2.7 Estimating Progressivity

The plots we have presented so far suggest that the tax and transfer system is progressive overall, but that different components of taxes and transfers contribute in very different ways to overall progressivity or regressivity. To summarize these contributions in a quantitative way, we now approximate the tax and transfer system using the parametric functional form used by Benabou (2002), Heathcote, Storesletten, and Violante (2017a) and many others. This approach provides a simple one-dimensional measure of tax progressivity that facilitates comparisons across states and over time and makes it easy to interpret the results. In this specification,

	All	1	2	3	4	5	6	7	8	9	10	Top 1%
Pre-Government Income	119,534	18,691	33,060	45,598	58,425	72,598	88,373	107,293	131,631	169,751	469,776	1,969,520
Wage and Salary Income	93,927	16,657	30,722	42,193	55,409	67,638	83,660	100,865	123,498	157,214	261,389	701,151
SOI Replaced (%)	8	0	0	0	0	0	0	0	0	0	83	100
Total Transfers	6,000	12,622	8,889	7,505	5,951	5,251	4,678	3,988	3,862	3,598	3,660	3,178
Federal Transfers	3,818	8,218	5,548	4,637	3,695	3,226	2,955	2,530	2,526	2,389	2,454	2,037
School Lunch	130	329	245	181	129	102	87	67	60	52	48	65
Veterans' Benefits	258	253	196	220	242	302	259	288	318	246	252	118
Survivors' Benefits	185	220	85	152	157	127	142	165	268	235	301	192
Disability Benefits	215	290	226	222	177	193	219	172	228	191	229	76
SS SI and DI Benefits	478	1,025	750	639	527	446	407	310	243	264	174	90
SS OA Benefits	422	517	475	428	433	387	379	358	371	436	432	484
SNAP	401	1,657	870	580	330	200	135	88	66	45	36	46
SSI	205	557	362	305	202	164	127	100	82	72	84	88
Housing Assistance	109	688	232	103	30	16	6	6	3	3	1	3
Medicare	666	1,089	904	798	687	603	625	506	456	476	521	483
State Transfers	857	1,621	1,229	1,093	877	808	711	618	559	540	518	420
Unemployment Insurance	187	307	213	198	196	171	174	153	145	171	145	75
Workers' Compensation	83	120	101	120	72	93	82	84	56	56	49	12
Alaska PFD	11	5	7	9	11	13	10	14	12	15	11	6
Joint Federal-State Transfers	1,325	2,783	2,112	1,775	1,379	1,217	1,013	840	777	669	688	721
TANF	31	101	46	33	20	30	25	18	16	7	12	33
Medicaid	1,294	2,682	2,066	1,742	1,359	1,187	987	822	761	662	677	687
Income Taxes	22,759	-2,145	-66	2,466	4,800	7,306	10,092	15,876	23,159	32,882	133,185	674,957
Federal	18,104	-2,250	-597	1,486	3,395	5,457	7,653	12,678	19,131	27,346	106,703	536,448
State & Local	4,656	105	531	980	1,405	1,850	2,438	3,197	4,028	5,536	26,482	138,509
FICA	12,419	2,626	4,648	6,384	8,174	10,097	12,320	14,842	18,036	22,109	24,956	41,647
Consumption Taxes	3,259	1,782	2,084	2,319	2,577	2,877	3,172	3,504	3,903	4,419	5,955	11,903
Federal	448	293	344	371	400	432	463	496	517	538	621	964
State	2,812	1,489	1,740	1,948	2,177	2,445	2,710	3,008	3,386	3,881	5,333	10,939
Sales	1,838	864	1,019	1,159	1,327	1,516	1,712	1,934	2,247	2,670	3,937	8,869
Excise	973	625	722	789	850	929	998	1,074	1,139	1,211	1,397	2,070
Property Taxes	2,709	1,480	1,580	1,698	1,823	1,958	2,141	2,416	2,658	3,230	8,109	19,717
Owners	3,272	1,938	1,921	1,970	2,054	2,174	2,333	2,608	2,837	3,437	8,539	20,750
Renters	1,717	1,209	1,309	1,413	1,530	1,599	1,721	1,868	2,035	2,282	5,717	13,539

Table 3: Distribution of taxes and transfers in our baseline sample, 2015/2016. This sample selects ASEC households with heads aged between 25 and 60 and one spouse earning at least $7,250 (minimum wage part-time work).

The column labelled "All" reports average income and tax and transfer values for the entire sample. The columns labelled "1" through "10" correspond to deciles of households ranked by household pre-government income, where each decile bin contains about the same (weighted) number of households. The column labelled "Top 1%" refers to the one percent of households with the highest incomes. All variables are in current $ except for "SOI Replaced" which indicates the share of ASEC households in each decile for whom income and tax variables are imputed using IRS SOI data. Local income taxes are included in state income taxes for SOI replaced households and households residing in Indiana, Maryland or New York.

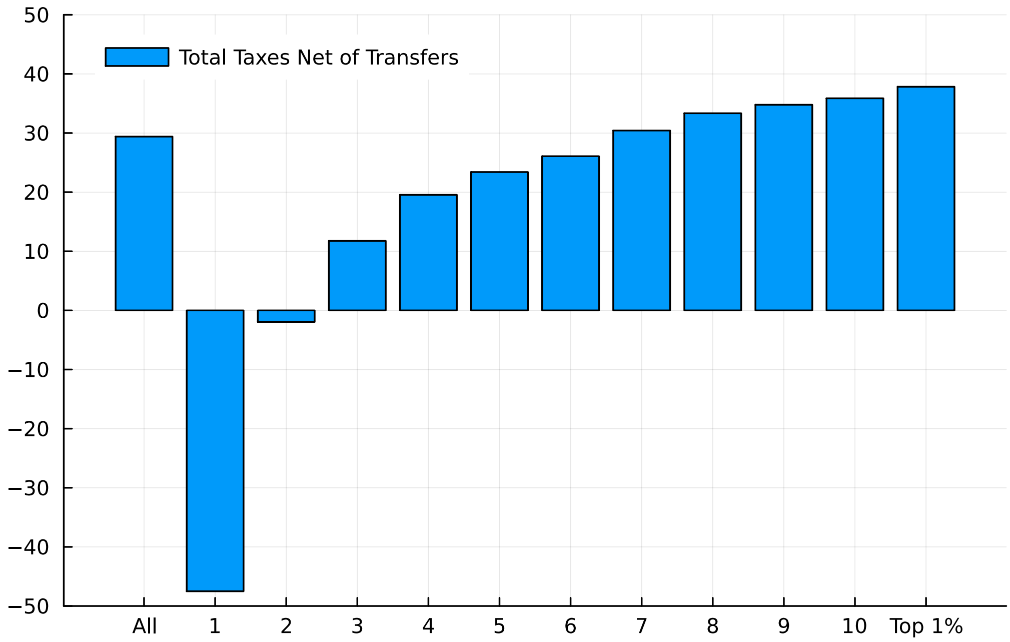

Figure 9: Average total tax (total taxes net of transfers) rates. 2015/2016. See notes to Figure 1.

income after taxes and transfers, $y - T(y)$, is related to pre-government income y according to:

$$\log(y - T(y)) = \lambda + (1 - \tau) \log(y), \tag{2}$$

where the coefficient τ indexes progressivity.

As in Heathcote, Storesletten, and Violante (2017a), we estimate τ by running least squares regressions on our cross-sectional ASEC sample given household level values for y_i and $y_i - T_i$.[26] But here we will consider a range of different measures of T_i, corresponding to different subsets of taxes and transfers. Each different measure will generate a different estimate for τ.

First we include only federal taxes and transfers in T_i and estimate a coefficient for federal progressivity, τ^f. Then we do the same thing, but using only state and local taxes and transfers to estimate state progressivity, τ^s. Finally we include all taxes and transfers to estimate overall progressivity τ.[27]

[26] Note that pre- and post-government income appear in logs in our estimating equation. Thus, we must drop households for whom either income is negative. Fortunately, this is a negligible fraction of households in our baseline sample: we drop at most 0.04 percent of households.

[27] Contrary to Heathcote, Storesletten, and Violante (2017a) we do not subtract deductions and exemptions from our income measures in this estimation (we do, of course, incorporate how they impact taxes paid). The reasons are twofold. First, it is difficult to accurately measure deductions in the ASEC data because Adjusted Gross Income and Taxable Income are both top-coded. Second, our focus is on measuring redistribution (rather than quantifying distortions), and for quantifying redistribution the gap between *total* income before and after taxes and transfers is more relevant than the gap between *taxable* income.

	T_i measure	τ estimate
Federal	Income Taxes	0.104
	- Transfers	0.198
	+ Excise Taxes	0.195
State	Income Taxes	0.013
	- Transfers	0.038
	+ Property Taxes	0.019
	+ Sales Taxes	0.006
	+ Excise Taxes	-0.004
Federal & State		0.202

Table 4: Estimates for progressivity τ from the pooled national sample. Estimates refer to 2015/2016 and use ASEC household weights. Transfers include all transfers shown in Table 2. Federal & State includes all state and federal taxes and transfers. JF: I think we should explain why Federal and State does not sum up to Federal & State.

Table 4 reports overall estimates for federal and state tax and transfer progressivity. In the top part of the table we include only federal taxes and transfers. We find, as in Heathcote, Storesletten, and Violante (2017a), that the federal tax and transfer system is quite progressive. With only federal taxes, we estimate $\tau = 0.105$. Adding federal transfers raises τ to 0.198 and including federal excise taxes gives an estimate of 0.195. The baseline estimate in Heathcote, Storesletten, and Violante (2017a), who also focused on federal taxes and transfers, was slightly lower at $\tau = 0.181$. Note that in that paper we did not include Medicaid in our measure of transfers.

The middle panel of the table isolates the progressivity embedded in state taxes and transfers. To start, we include only state income taxes in our measure of post-government income, then add transfers, and then add, cumulatively, property taxes, sales taxes, and excise taxes. The message is that state income taxes, on average, are weakly progressive, while state transfers add a modest amount of redistribution. In contrast, property taxes, sales taxes, and excise taxes are all regressive, in the sense that when they are incorporated in the measure of post-government income, estimated progressivity declines. Overall, state tax and transfer systems are close to proportional on average, with an estimated τ of -0.002.

Figure 10 is a visual illustration of the progressivity embedded in federal taxes and transfers (left panel), and the near proportionality of state taxes and transfers (right panel).[28]

[28]Note that the Benabou-HSV log-linear functional form does not perfectly the observed relationship between pre-government income and disposable income. The fit is slightly worse than in Heathcote, Storesletten, and Violante (2017b) because our transfer measure here is broader, translating to higher disposable income at low income

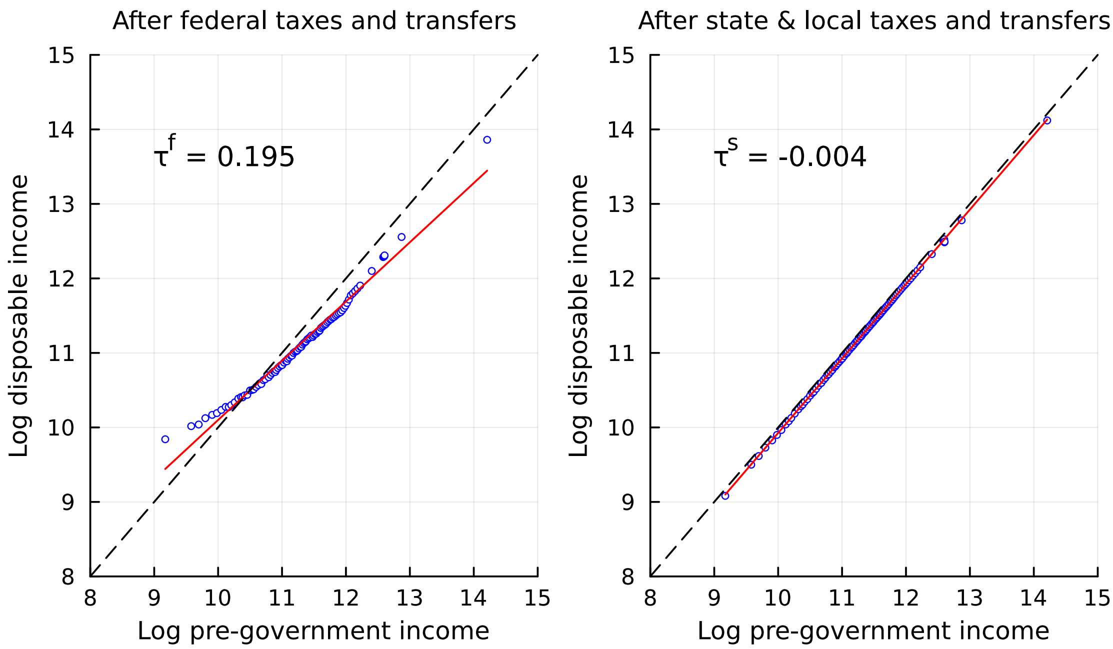

Figure 10: Fit of the log-linear Benabou-HSV tax and transfer function. Left panel: T_i includes federal taxes and transfers. Right panel: T_i includes state taxes and transfers. Each dot corresponds to one percent of the baseline 2015/2016 sample, ranked by pre-government income. Estimation uses ASEC household weights.

Figure 11 translates these τ estimates (and the corresponding λ estimates) into profiles for marginal and average tax rates. The blue lines show tax rates implied by federal taxes net of federal transfers. The red lines show the effect of adding state income taxes net of transfers, which increase marginal tax rates by around 5 percentage points. The green lines add property and consumption taxes. These mostly increase tax rates at lower income levels, reflecting the fact that these taxes are regressive.

levels.

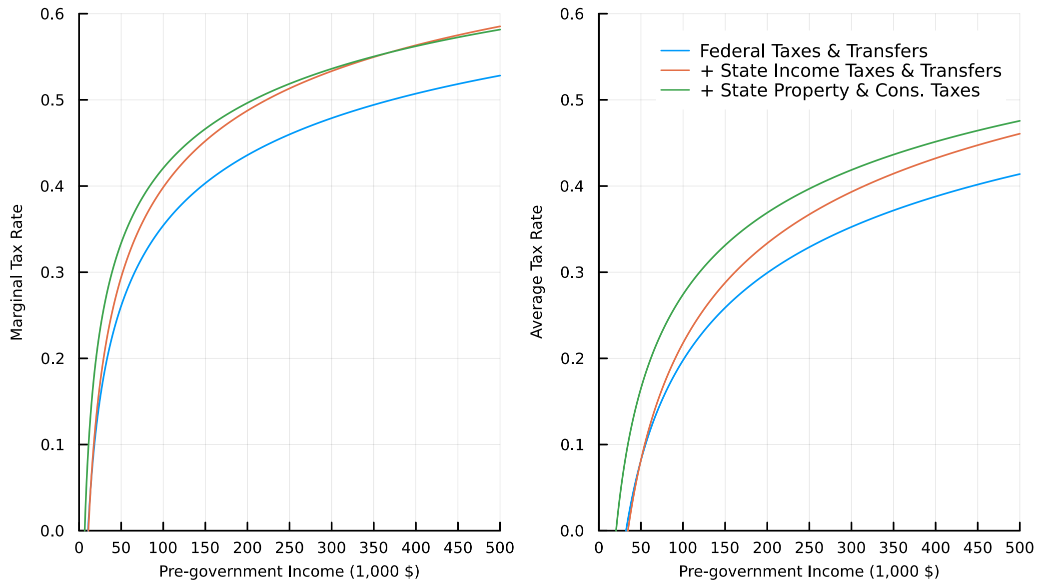

Figure 11: Average economy-wide marginal and average tax rate schedules for different measures of taxes and transfers. The blue line includes all federal taxes and transfers. The red line adds state and local income taxes and state transfers. The green line adds state and local property, sales and excise taxes.

2.7.1 Robustness Estimating Progressivity

One critique against the simple one-dimensional measure of progressivity that we focus on in our main analysis, is that it misses variation in progressivity across the income distribution, especially at the bottom end. Ferriere, Grübener, Navarro, and Vardishvili (2023) shows that the fit to the empirical the tax and transfer system can be significantly improved by simply adding a lump-sum transfer to our benchmark log-linear tax and transfer system. In this specification, income after taxes and transfers, $y - T(y)$, is related to pre-government income y according to:

$$y - T(y) = \lambda(y)^{1-\tau} + T, \tag{3}$$

where the redistribution is now characterized by both progressivity coefficient τ and the lump-sum transfer T. We will allow for heterogeneity across states in all these parameters.

Another possible weakness of our estimation is, as we shall see, that we overestiamte the tax progressivity for the very top percentiles of income. By estimating the tax progressivity as an OLS regression of log of post-government income on log of pre-government income, the top earners get relatively low weight in the regression even though they provide a large share of aggregate tax revenue. König (2023) considers an alternative estimation, based on PPML, that puts much more weight on the top percentiles of income. As a robustness check, we also consider a PPML estimation of tax progressivity.ZZZKS ANALYSIS MUST BE ADDED

3 Cross-State Variation in Average Tax and Transfer Rates

We next turn to exploring differences in tax and transfer rates, and in overall net tax progressivity, across U.S. states.

3.1 Reweighting State Income Distributions

U.S. states differ in terms of their pre-government income distributions, in addition to featuring different tax and transfer systems. To isolate cross-state differences in taxes and transfers, we henceforth reweight household observations state by state, so that the reweighted state income distribution for each state resembles the national distribution. In particular, we record pre-government income values at each decile of the national pre-government income distribution to construct 10 income bins. Then, for each state, we compute scaling factors for households within each national income bin, such that when we rescale the original ASEC weights by those factors, 10 percent of reweighted state households lie within each bin. See Appendix I for more details.[29]

3.2 Cross State Variation in Income, Consumption and Property Tax Rates

We start by describing cross-state variation in terms of what states choose to tax (income, consumption or property) and variation in overall effective tax rates. The fact that different states rely on different types of taxes to fund operations will turn out to play an important role in our subsequent analysis of cross-state variation in state tax and transfer progressivity.

Figure 12 plots state and local average values for (i) income taxes, (ii) sales and excise taxes, and (iii) property taxes. In this and also similar subsequent figures, we use a $*$ superscript to denote states that have no state income tax, and a $\wedge$ superscript to denote states that have no

[29]If the tax and transfer system in each state was perfectly represented by equation (2) then one could safely estimate state-specific values for progressivity τ by least squares without reweighting. In practice, of course, this simple specification does not perfectly fit the data (see Figure 10). As a result, absent reweighting, one might expect to estimate higher values for τ in states with more poor households, even if tax and transfer rules were identical across states.

state sales tax.

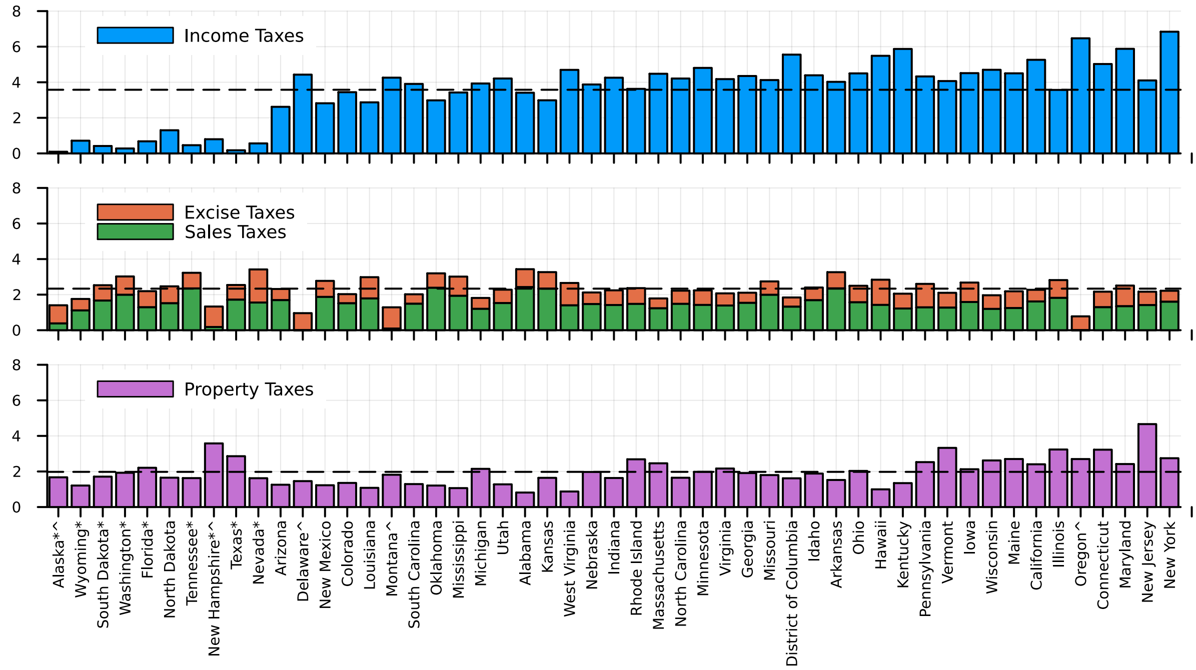

Figure 12: Average tax rates by state. The horizontal lines indicate national averages. A $*$ superscript denotes states that have no state income tax, and a $\wedge$ superscript denotes states that have no state sales tax. ASEC baseline sample, 2015/2016

Figure 13 stacks the components just described and also adds transfers (which enter with a negative sign). The state level net tax rate – total estimated state tax revenue less transfers divided by state income – is the sum of all these components. In both Figures 12 and 13 states are ordered left to right from the one with the lowest net tax rate (Alaska) to the one with the highest (New York).

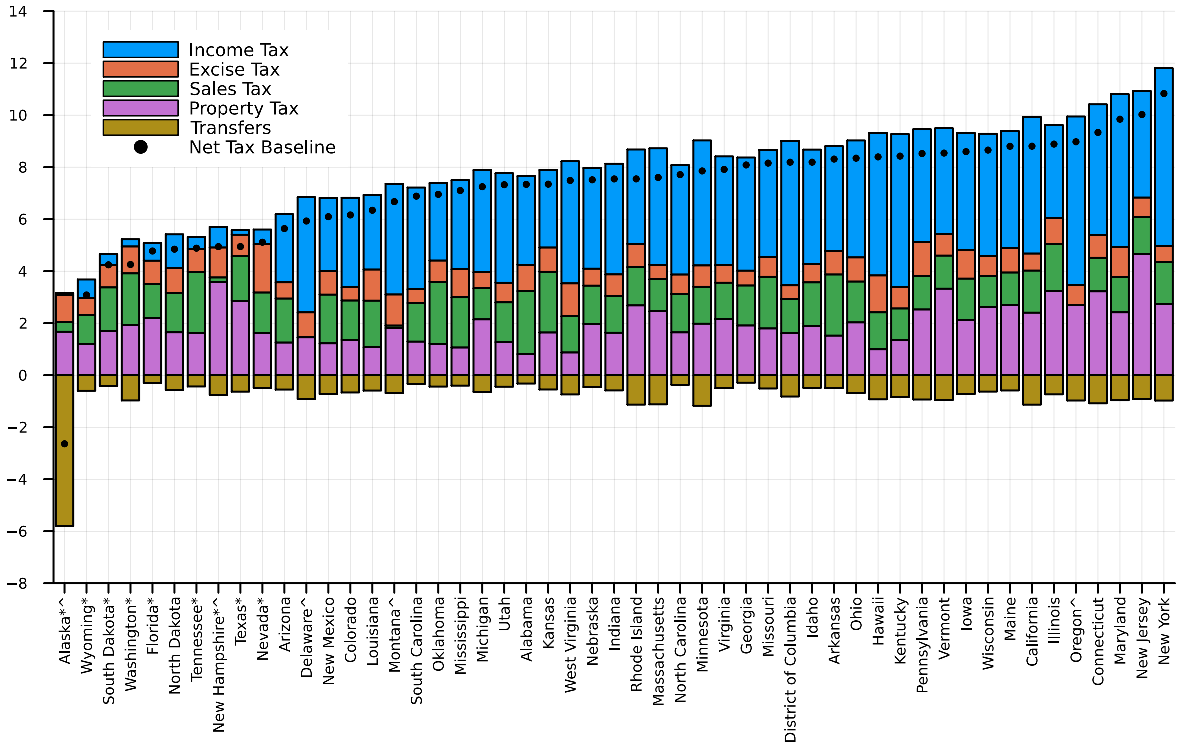

Figure 13: Average tax and transfer rates by state. A $*$ superscript denotes states that have no state income tax, and a $\wedge$ superscript denotes states that have no state sales tax. ASEC baseline sample, 2015/2016.

The first clear message is that net tax rates vary enormously across states. Net taxes are negative in Alaska, but nearly 12 percent of household income in New York.

Second, states that do not levy income taxes tend to have much lower average net tax rates overall. Nine states — Alaska, Florida, Nevada, New Hampshire, South Dakota, Tennessee, Texas, Washington and Wyoming — do not levy a state income tax.[30] They constitute nine out of the ten states with the lowest overall net tax rates.[31] Figure 12 illustrates that states with zero or low income tax rates do not offset lost revenue via systematically higher sales or property taxes. New Hampshire does have relatively high property tax rates, but it also has no state sales tax.

Third, states that have state sales taxes all collect quite similar shares of income via consumption taxes. New Hampshire, Oregon, Montana, Alaska and Delaware (the NOMAD states)

[30] New Hampshire does not tax labor earnings, but it does tax interest and dividend income.

[31] The reason that state income tax revenue is not exactly zero in these states is that the IRS-SOI tabulations do indicate a small positive amount of state income taxes paid by residents of these states. That in turn reflects the fact that households counted as resident in states without state income taxes can also earn income in other states that is taxed at the state level.

have no state-wide sales taxes, and as a result are clear outliers.[32]

Fourth, there is large cross-state variation in property tax revenue, and states with the highest taxes overall tend to levy high property taxes. New Jersey is the prime example, but New York, Illinois and Connecticut also raise substantial revenue from taxing property.

Fifth, state transfers vary quite a bit across states, but they account for a relatively small share of income in all states except for in Alaska, where the Alaska Permanent Fund Dividend is large and drives the net tax rate negative. Putting aside Alaska, low tax states also tend to be relatively low transfer states, while state transfers tend to be a bit larger in the states with the highest state tax burdens.

3.3 California versus Texas

We now turn to discuss variation in progressivity at the state level. Before turning to state level estimates of the progressivity parameter τ, we first contrast the two largest states in the United States, which have quite different tax and transfer systems: California and Texas.

Figure 14 plots taxes paid, as a share of pre-government income, for each quintile of the U.S. pre-government income distribution, as well as for the top one percent, in 2015 and 2016. California is blue, and Texas is red (naturally). The top left panel indicates that California has a strongly progressive state income tax, while Texas has no state income tax. The top middle panel shows that sales and excise taxes were similar in the two states across all income bins.[33] Conversely, property taxes (top right) were slightly higher in Texas.[34]

Transfers (bottom middle) were much larger in California than Texas, especially at the bottom of the household income distribution. What accounts for this difference? First, California had a larger fraction of residents collecting unemployment insurance benefits, and UI benefits were also higher per recipient. Second, California had a much larger fraction of residents receiving Medicaid benefits.

The bottom right panel of Figure 14 plots total state taxes net of transfers. It is very clear from this plot that California and Texas have radically different tax systems. The California system is quite progressive, with net tax rates rising strongly with income. The Texas system, conversely, is quite regressive, with the poorest households facing the highest net tax burden. The reason

[32] Figure **??** in Appendix XX plots the standard state sales tax rates in 2016 (red bars), along with the within-state average local sales tax rates.

[33] The standard sales tax rate in Texas in 2015 was 6.25% compared to 7.50% in California.

[34] Recall that we do not include corporate income taxes in our baseline measure of taxes. California had a corporate income tax rate of 8.84% in 2015 and 2016, while Texas had no corporate income taxes.

California is so much more progressive is clear: they have a strongly progressive state income tax, and strongly progressive transfers. Texas, conversely, relies on regressive consumption and property taxes to fund state government.

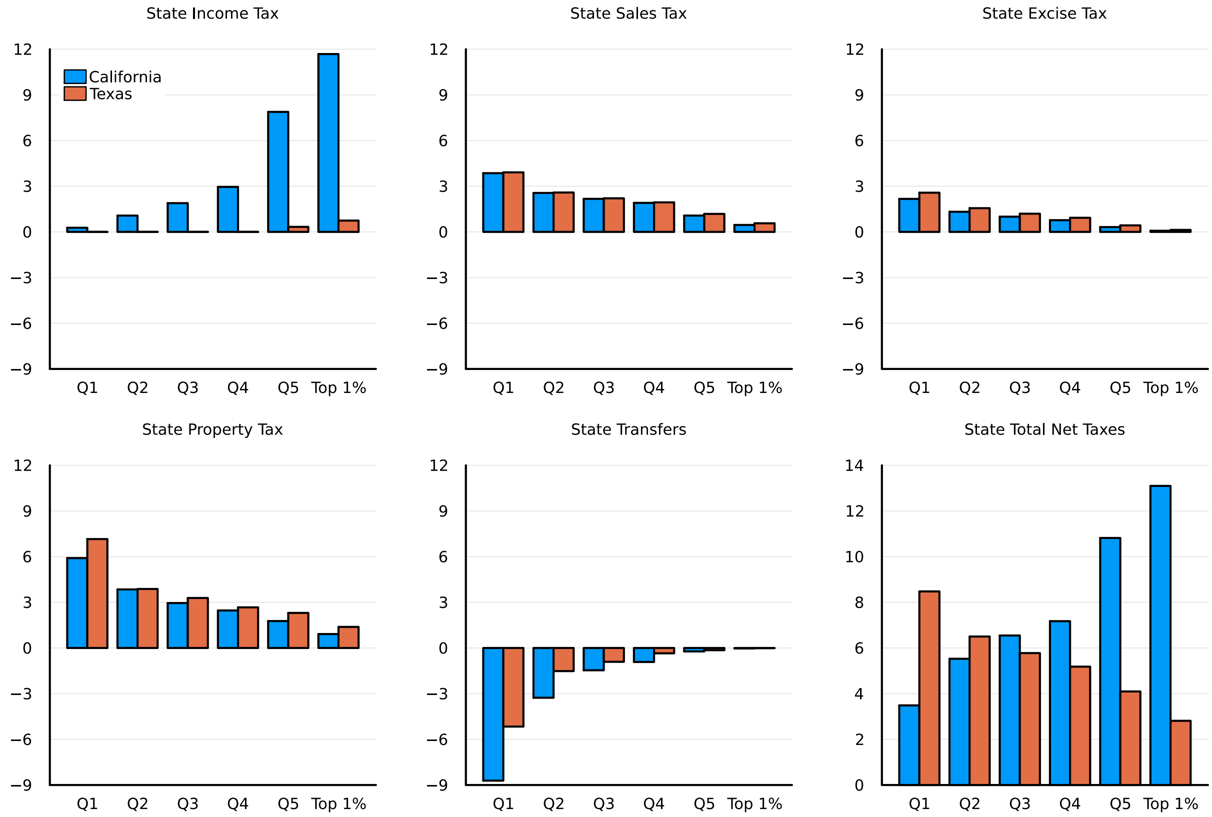

Figure 14: Average tax and transfer rates for California and Texas, 2015/2016. The plot shows state and local taxes paid and transfers received across five quintiles of the state pre-government household income distribution and for the top one percent (after re-weighting as described in Section 3.1).

Figure 15 plots the combined burden of federal and state taxes across the income distribution for California and Texas. The pattern of more overall redistribution in California is preserved: net transfers are larger at the bottom of the income distribution, and net taxes are larger at the top. Note that *federal* transfers at the bottom are also larger in California than in Texas. The reason is that because California spends more state money on Medicaid, it also receives more federal matching dollars.

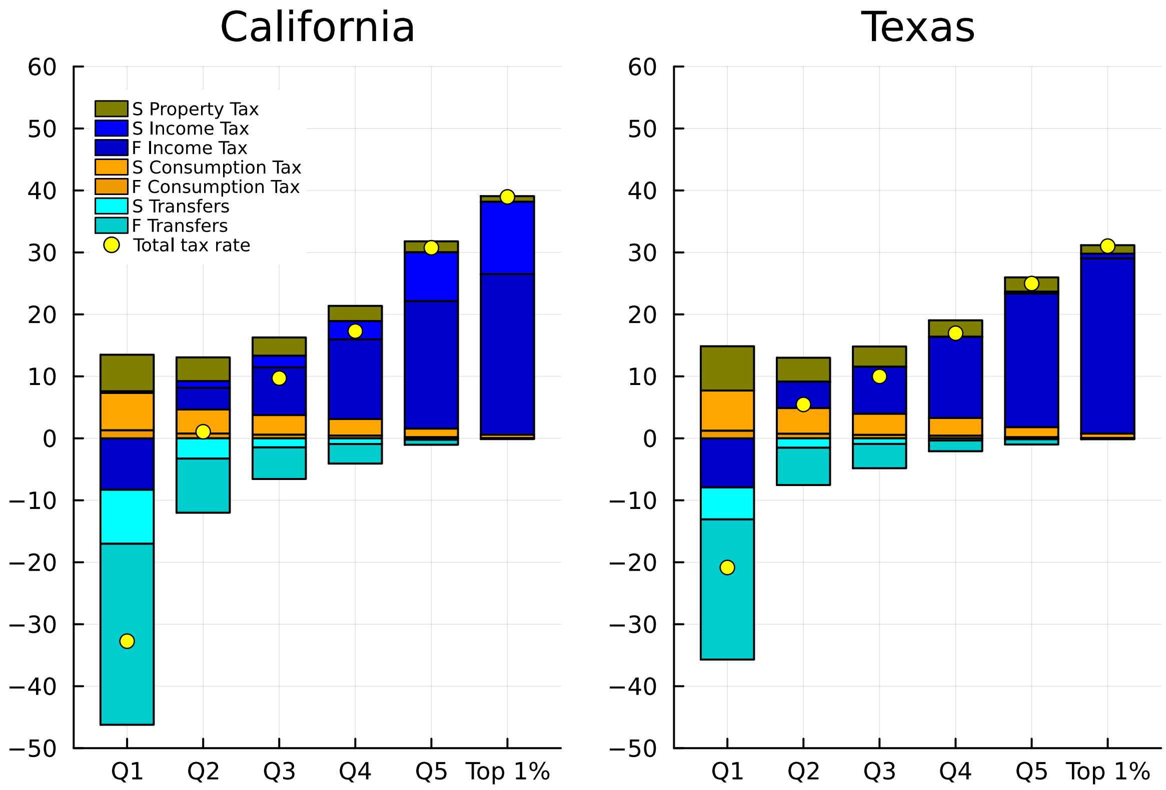

Figure 15: Average state and local as well as federal tax and transfer rates for California and Texas, 2015/2016. The plot shows state and local (S) as well as federal (F) taxes paid and transfers received across five quintiles of the state pre-government household income distribution and for the top one percent (after re-weighting as described in Section 3.1).

3.4 State Level Progressivity Estimates

Figure 16 plots estimates for the progressivity of state taxes and state transfers, τ^s, for all U.S. states. States are ranked from the least to most progressive.

Alaska has the most progressive state tax and transfer system, by our measure, thanks primarily to the APFD transfer. Illinois is the most regressive state. We have also computed the Suits (1977) Index for state taxes and transfers, which also provides a summary statistic for progressivity. The rank correlation between our τ^s estimates and the Suits index is 0.87, indicating that alternative measures deliver a very similar ranking.[35]

[35] We exclude Alaska from computing the rank correlation as the Suits Index is not suited for tax systems which deliver net transfers. Our progressivity ranking has a strong negative rank correlation with the ITEP Tax Inequality Index. Let's report what that correlation is please compute it Jon. Will do In 2024, the five states at the bottom of the ITEP ranking were California, New York, Vermont, Minnesota, and D.C. The five at the top were Florida, Washington, Tennessee, Pennsylvania, and Nevada. ITEP places Alaska as a relatively regressive state, because it ignores transfers. Other states with notably different rankings are New Jersey, Virginia, Michigan and Hawaii.

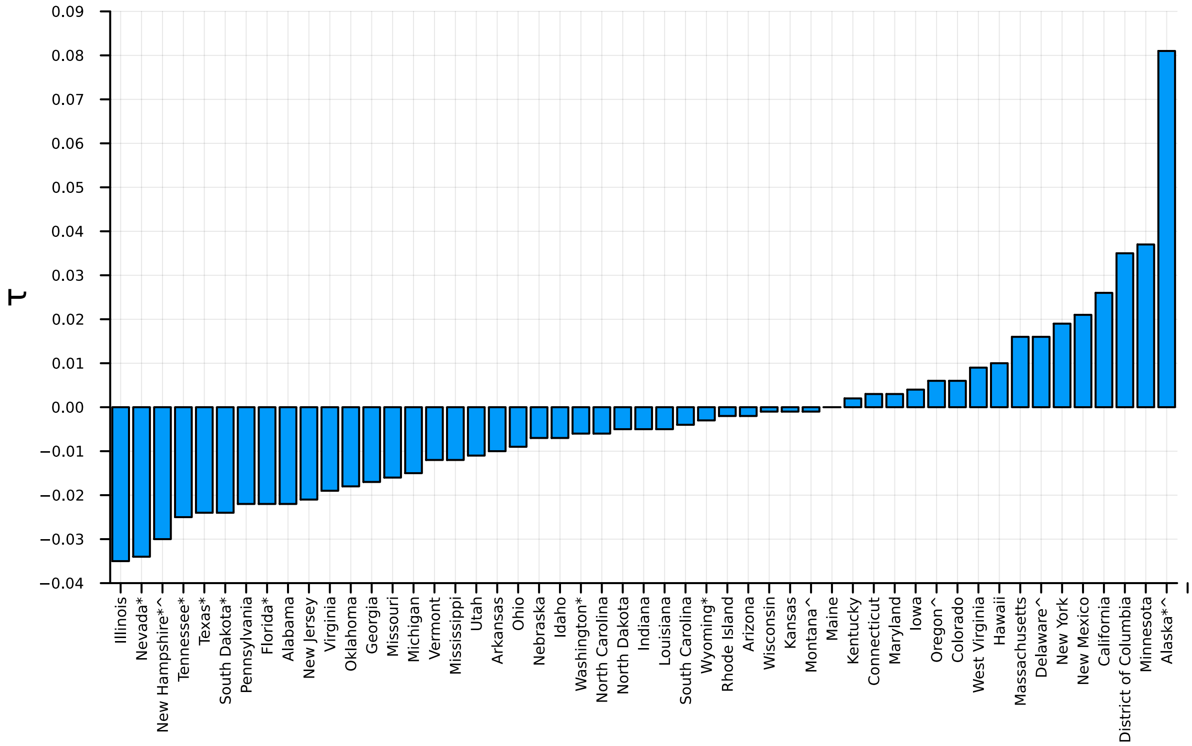

Figure 16: State level estimates of the tax and transfer progressivity parameter τ^s. Taxes and transfers include all state and local taxes and transfers but no federal taxes or transfers. Estimates are for 2015/2016.

Figures 16 and 18 plot contributions to progressivity from different types of taxes and from transfers for each state (see Section 2.7).[36] Transfers contribute positively and significantly to progressivity, with significant variation across states. In particular, transfers deliver much more redistribution in Alaska, Minnesota and the Northeast than in the rest of the country. State income taxes contribute positively to progressivity in all states, but the progressivity of those taxes varies across states, and is near zero in the states that do not levy state income taxes.

Other state taxes are regressive. Property taxes are especially regressive. In fact, if they did not levy property taxes, almost all states would have progressive tax and transfer systems. Property taxes are particularly regressive in New Jersey, New Hampshire, Vermont and Connecticut, reflecting the high property tax rates in those states (see Figure 12). That knocks those states down the overall progressivity ranking. Sales taxes are similarly regressive in all states that levy them, and excise taxes are regressive everywhere.

[36]For example, the contribution of sales taxes to progressivity in New Hampshire is estimated by regressing log household pre-government income minus sales taxes for New Hampshire households on a constant and log pre-government household income.

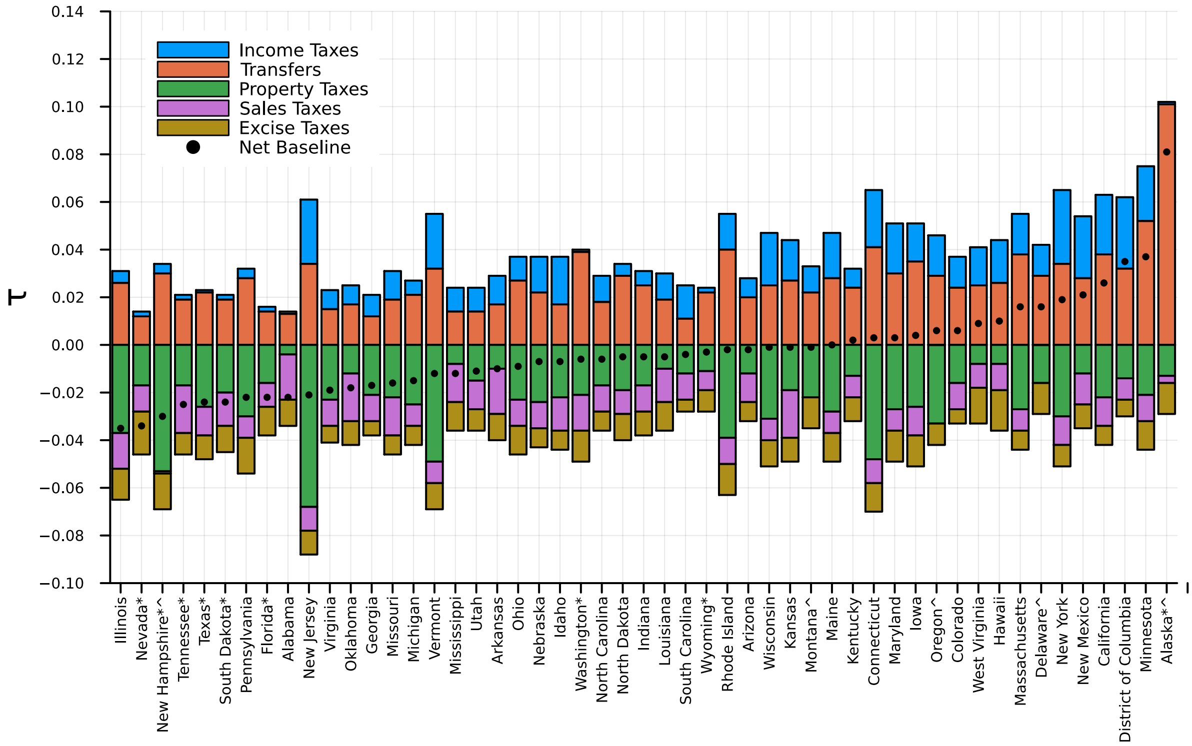

Figure 17: State τ^s decomposition. The plot shows estimates for progressivity induced by each of the state level taxes and transfers indicated in the legend, considering one tax at a time, using household weights constructed as described in appendix I. The black dots report overall state progressivity as reported in Figure 16. Estimates are for 2015/2016.

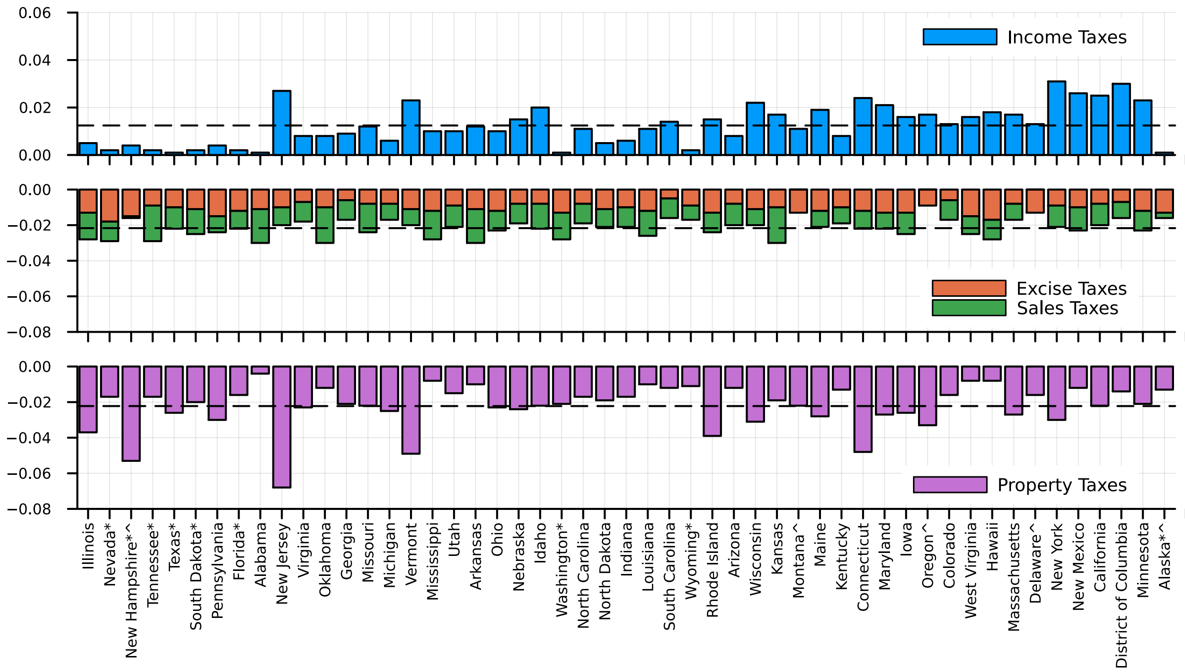

Figure 18: State level progressivity (or regressivity if negative) from income, consumption and property taxes. Horizontal lines are national averages. Estimates are for 2015/2016.

Figure 19 plots the geography of our τ^s estimates, with more progressive states colored in darker shades.

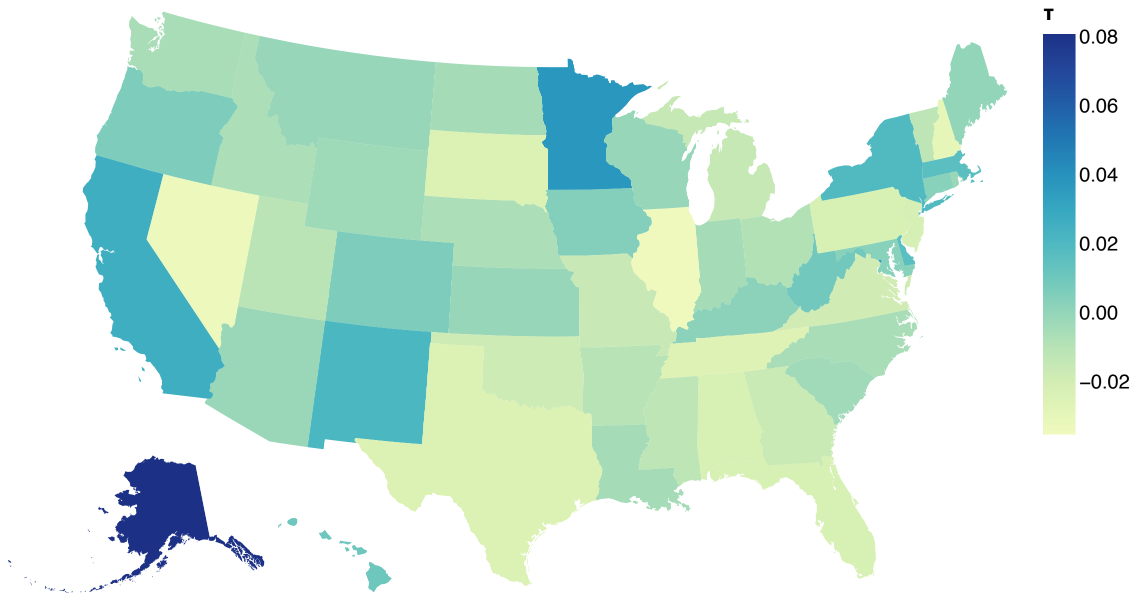

Figure 19: Map of τ^s estimates. 2015/2016.

Figure 20 plots average state net tax rates (Figure 13) against our state-level estimates for progressivity τ. There is a positive correlation: states with a higher net tax burden tend to have more progressive taxes. Illinois and New Jersey are the main exceptions to this pattern, reflecting their heavy reliance on regressive property taxes.

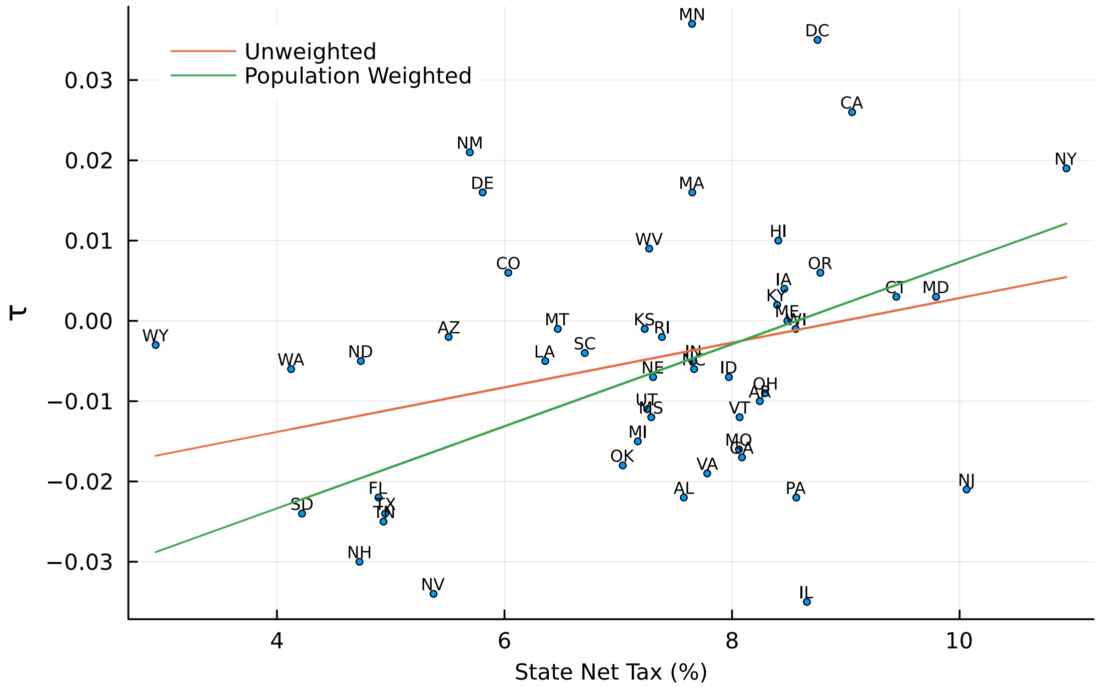

Figure 20: Comparison of state average net tax rates and estimated state tax progressivity τ^s. Alaska is excluded. Estimates are 2015/2016. The red line is the least squares best fit when states are weighted equally. The green line is the least squares best fit when states are weighted by population.

3.5 Time Variation in State Progressivity

We estimate state tax and transfer progressivity for three periods in which we pool adjacent sample years: 2005/2006, 2010/2011 and 2015/2016. Figure 21 shows the cross-sectional distribution of estimated state progressivity for the three periods.

Progressivity appears generally higher in 2010/11 than in the other years. The reason is that the unemployment rate was notably higher during this period: in the aftermath of the Great Recession, the national unemployment rate was around 9% in 2010/11 but below 5% in other sample years. In response to higher unemployment rates (and longer unemployment spells), some states expanded the generosity of unemployment insurance, in particular by extending the maximum duration of benefit eligibility, allowing recipients to keep receiving assistance for longer than in other years.[37]

Between 2010/11 and 2015/16 the share of Americans covered by Medicaid increased substantially, thanks to the Affordable Care Act. However, while some states opted to expand Medicaid insurance prior to 2015/16, others did not. This explains the widening in estimated τ^s dispersion visible in the green kernel density plotted in Figure 21 relative to the blue and red ones. See Appendix J for more results and details.

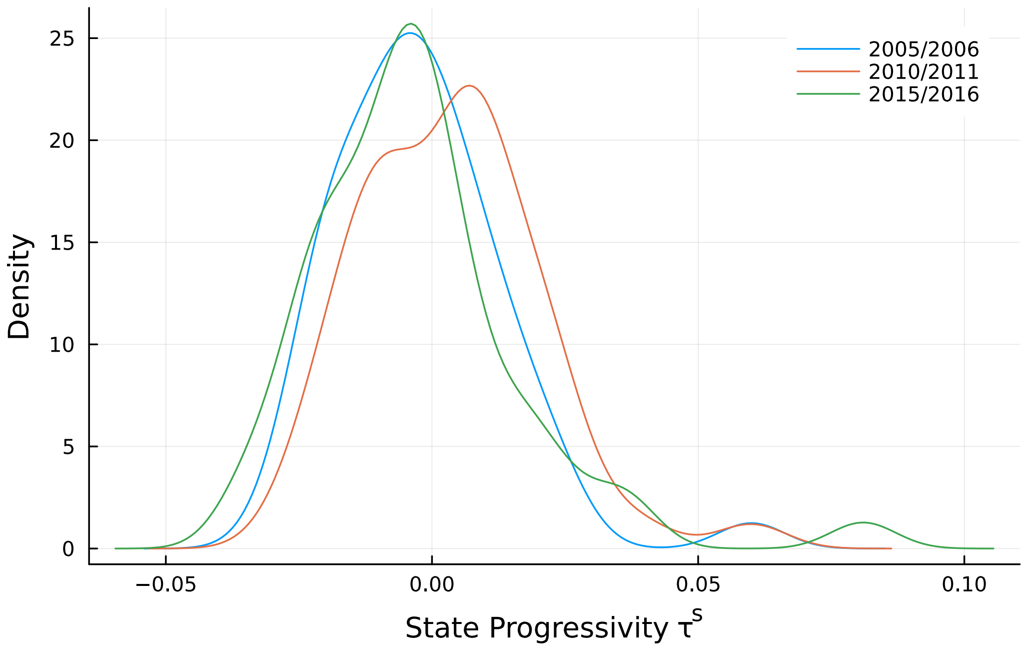

Figure 21: Kernel density estimate of state progressivity, τ^s. Estimates use all state taxes and transfers discussed in Section 3.4.

4 Extension 1: Including Corporate Income and Business Taxes

In addition to the taxes we include in our baseline analysis (personal income, property, sales and excise taxes), state and local governments collect a range of other taxes, as shown in Appendix A. One is the corporate income tax which is also collected by the federal government. While federal tax corporate income tax collections amounted to about 1.5% of U.S. GDP in 2016, state collections only represented about 0.2% of state GDP, on average. However, cross-state variation is significant as some states do not levy corporate income taxes at all, while others collect between 0.5 and 1% of state GDP.

In addition, a considerable portion of total state and local tax collections are levied on busi-

[37]Through the Emergency Unemployment Compensation program, the federal government provided additional extensions. We assign these benefits to state governments as they are not separately reported in the ASEC data.

nesses, for example through property taxes and sales taxes on business inputs. Figure 31 in Appendix A indicates that, across all states, almost half of total state and local tax collections come from businesses rather than households. Again, cross-state variation is considerable as the business share ranges from 30% to 75%.

We therefore now extend our analysis of state tax progressivity by including state (and federal) corporate income taxes and other state and local taxes collected from businesses. However, since these taxes are not paid directly by households, imputing them into our dataset requires making assumptions on how they are ultimately passed through to households at different points in the income distribution. These incidence assumptions will obviously affect our state progressivity estimates. An additional challenge is that the income categories most closely tied to the incidence of these taxes – business and dividend income – are known to be especially severely under-reported in both survey and tax returns data, which are the basis for the SOI tables we use to augment information on high-income ASEC households. As a result, the base for these taxes is low in our sample.

Our goal is to provide estimates of state tax progressivity which incorporate the majority of state and local taxes. Hence, despite these challenges, we now include corporate income and business taxes in an extension to our analysis to see how they affect the level and spatial variation of our progressivity estimates. In the following two sections, we provide brief summaries on how we impute these taxes into our dataset while Appendices L and M have more comprehensive descriptions.

4.1 Corporate Income Taxes

In addition to the federal corporate income tax, some states levy an extra corporate income tax (or corporate franchise tax) on businesses operating within the state. Corporate income taxes fall directly on firm owners, depressing after-tax cash flows and thus dividends or capital gains. However, to the extent that employee compensation is tied to firm profits, part of the incidence of corporate income taxation also falls on labor.

We assume that 60 percent of corporate income taxes fall on firm owners, while 40 percent fall on workers' earnings, based on a summary of the existing literature.[38] Based on these same studies, we also take into consideration that the incidence on labor is extremely unequal and posit that half of the labor share (i.e. 20 percent of the total tax) accrues to households in the

[38]See Serrato and Zidar (2016); Kline, Petkova, Williams, and Zidar (2019); Lamadon, Mogstad, and Setzler (2022); Dobridge, Landefeld, and Mortenson (2021); Dobridge, Kennedy, Landefeld, and Mortenson (2023)

top 1% of the labor earnings distribution, while the other half falls on households between the 75th and 99th percentiles of the distribution.

For *federal* corporate income taxes, we measure total corporate income tax revenue, and allocate 60 percent of the total across U.S. households in proportion to dividend income. We then allocate 20 percent of the total to households in the top 1% of U.S. households ranked by wage and salary income, in proportion to that income, and do the same for the remainder of the top quartile.

For *state* corporate income taxes, we allocate 60 percent of the state total across *all* U.S. households in proportion to dividend income, under the assumption that business ownership is geographically dispersed. However, we allocate the 40 percent of state corporate income taxes that falls on labor to households resident in the same state, in proportion to household labor earnings, as described above.

Figure 22 reports the resulting effective corporate income tax rates across the income distribution. Given our incidence assumptions, this is a very progressive tax as dividend income is heavily concentrated at the top of the household income distribution.

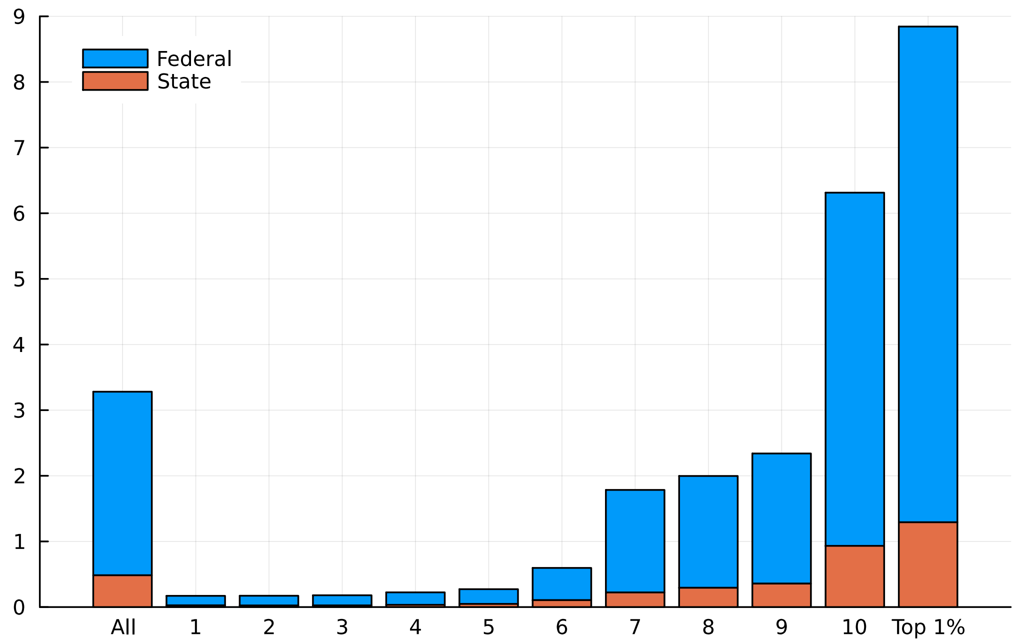

Figure 22: Average corporate income tax rates (Federal, State) for 2015/2016. Rates are plotted for all households, for 10 deciles of the household pre-government income distribution, and for the top 1 percent of households by income. For each bin, tax rates are computed as average taxes paid divided by average within-bin pre-government income. The tax and income values are reported in Table 6 in Appendix C.2.

4.2 Business Taxes

Our main data source for state-level business tax revenues is a series of reports called *Total state and local business taxes, State-by-state estimates* compiled by Ernst & Young LLP in conjunction with the Council On State Taxation and the State Tax Research Institute (Ernst and Young, 2016). These reports contain, for each state and year, estimates of state and local tax revenue paid by businesses based on data from the Census of State and Local Government Finance. The individual state income tax on business income, state corporate income tax, and unemployment insurance tax are already included in our previous calculations. We classify the remaining taxes paid by businesses into two groups: intermediate taxes (which includes sales and excise taxes on intermediate inputs, and license taxes) and property taxes.

To compute the incidence of these two taxes on households, we follow the strategy outlined in the most recent version of the *Minnesota Tax Incidence Study* (Minnesota Department of Revenue: Tax Research Division, 2024) which is widely regarded as the gold standard for state-level tax incidence studies. Since taxes on short-lived intermediate business inputs directly raise the cost of production, we assume that their incidence is shifted forward either to local labor (via lower wages) or to local consumers (via higher prices) proportionately to the share of tradable and non-tradable output in the state, respectively. The logic is that, for non-tradables, the price is determined nationally and cannot be raised to accommodate the local tax. The implied tax rate on labor is applied proportionately to labor income to each household residing in the state. The implied tax rate on consumers is applied proportionately to non-tradable spending of each household residing in the state.

For property taxes, we assume that he land share of property taxes falls on business owners. We impute it to households residing in the state proportionately to their business income (which we use as a proxy for rental income because we do not observe rental income in ASEC). The residual property tax is treated as we did for revenues from taxes on intermediate inputs, i.e. we split it between the tradable share falling on workers and the non-tradable share falling on consumers. Appendix M provides more details.

The resulting tax rates of each category for different income groups in our dataset are shown in Figure 23 for 2015/2016.

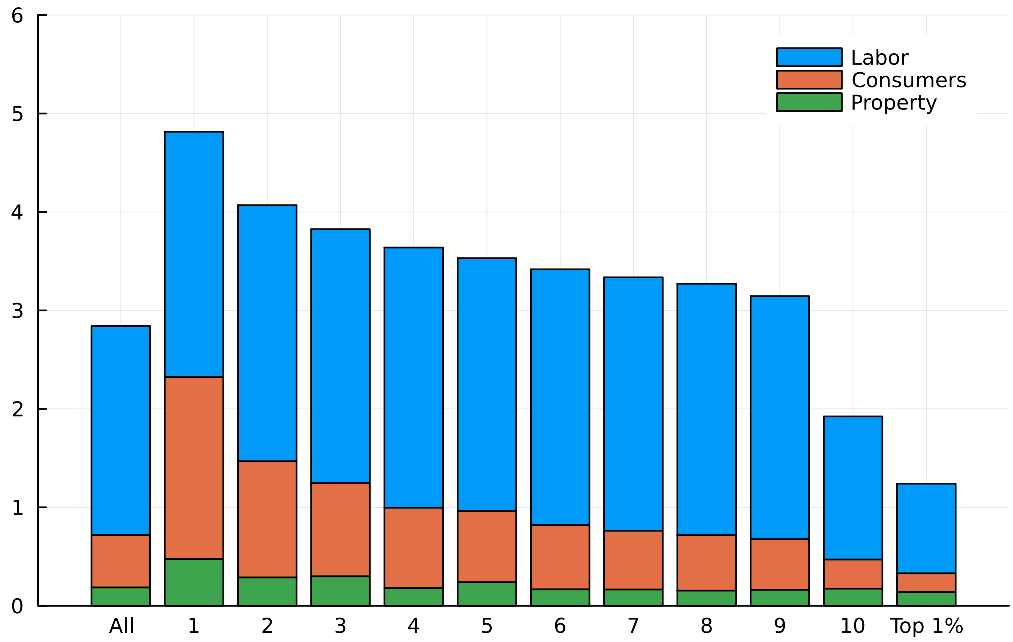

Figure 23: Average business taxes paid by pre-government income decile for 2015/2016. The plot decomposes taxes by their incidence on labor, consumer spending, and property income. See notes to Figure 22.

4.3 Results

Figure 24 adds corporate income and business taxes to the average tax and transfer rates shown in Figure 13 but retains the order of states according to the net tax rate which excludes them. Including these two additional taxes has two effects. First, the net tax rate increases in all states as the combined corporate income and business tax rate is positive and sizable in all states (the two taxes average about 0.5% and 3.8% respectively). Second, the increases are larger in states which previously had lower net tax rates, especially in those states without income taxes, indicating that those states rely more heavily on taxes collected from businesses. Hence, using the extended net tax rate to order states results in a different ranking of net tax burden, as some of the low net tax rate states climb the ranking. The Spearman rank correlation coefficient between the two different net tax rate measures is 0.70.

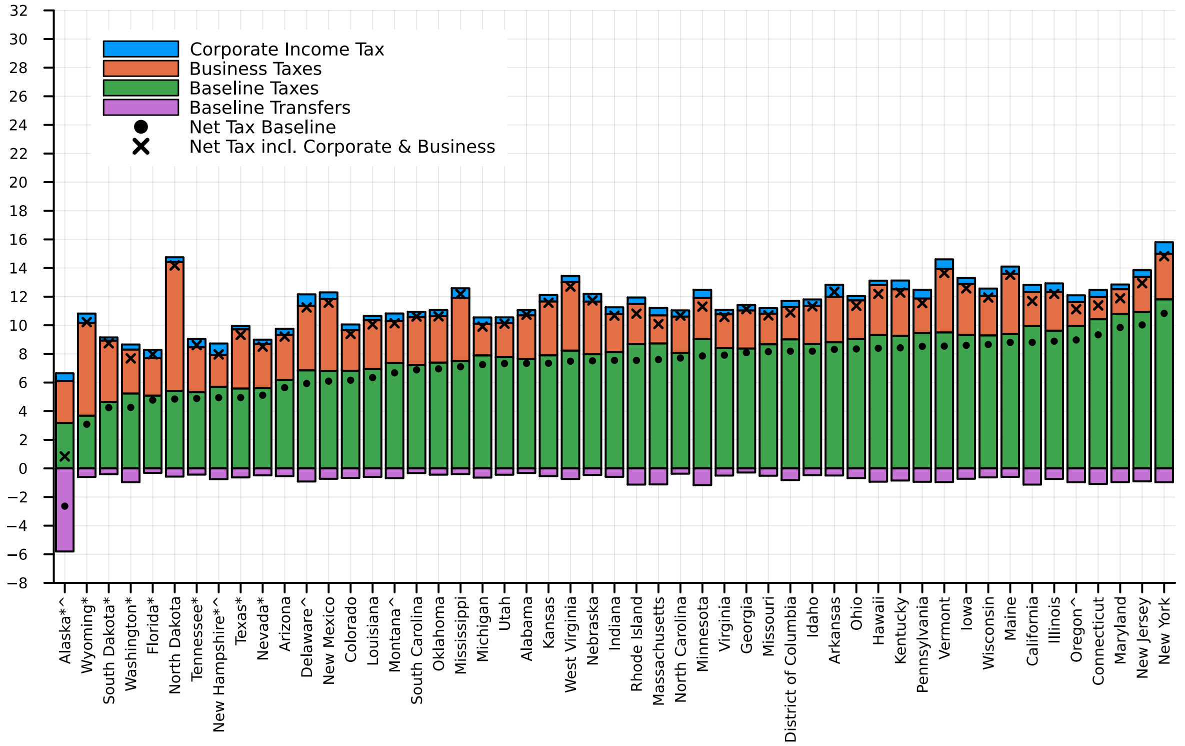

Figure 24: Average tax and transfer rates by state, excluding and including corporate income taxes and taxes collected from businesses. Baseline taxes includes income, excise, sales and property taxes. ASEC baseline sample, 2015/2016.

Using the additional taxes, we re-estimate the aggregate measures of federal and state tax progressivity reported in Table 4. As shown in Table 5, including corporate income taxes increases progressivity, reflecting the fact that these taxes are paid primarily by high income households, as shown in Figure 22. Other state business taxes, on the other hand, are regressive; including them more than offsets the progressivity increase from state corporate income taxes and results in state tax and transfer systems which are mildly regressive, Including all federal and state corporate and business taxes raises average progressivity from 0.204 to 0.224, reflecting the large positive contribution to progressivity from the federal corporate income tax.

Finally, we repeat the state level progressivity decomposition shown in Figure 17 to get a sense for how the corporate income and business taxes compare to the other taxes (and transfers). Figure 25 adds to the earlier decomposition corporate income and business taxes. In all states, corporate income taxes are progressive but the relative magnitude of their contribution is very small. Business taxes, on the other hand, are regressive in all states but their contribution differs substantially across states. In Vermont, North Dakota, Maine and New Mexico, business tax regressivity is especially large.

	Baseline				Extension 1			
	T_i measure	τ estimate	N unweighted (%)	N weighted (%)		τ estimate	N unweighted (%)	N weighted (%)
Federal	Income Taxes	0.104	170,866.33	99.95	Income Taxes	0.104	170,866.33	99.95
	- Transfers	0.198	170,916.35	99.98	- Transfers	0.198	170,916.35	99.98
	+ Excise Taxes	0.195	170,916.11	99.98	+ Excise Taxes	0.195	170,916.11	99.98
					+ Corporate Income Taxes	0.214	170,911.78	99.97
State	Income Taxes	0.013	170,954.54	100	Income Taxes	0.013	170,954.54	100
	- Transfers	0.038	170,954.54	100	- Transfers	0.038	170,954.54	100
	+ Property Taxes	0.019	170,949.76	100	+ Property Taxes	0.019	170,949.76	100
	+ Sales Taxes	0.006	170,949.76	100	+ Sales Taxes	0.006	170,949.76	100
	+ Excise Taxes	-0.004	170,945.8	99.99	+ Excise Taxes	-0.004	170,945.8	99.99
					+ Corporate Income Taxes	-0.002	170,945.8	99.99
					+ Business Taxes	-0.011	170,945.8	99.99
Federal & State		0.202	170,864.59	99.95		0.227	170,840.41	99.93

Table 5: Estimates for progressivity τ from the pooled national sample. Estimates refer to 2015/2016 and use ASEC household weights. Extends the baseline estimation results shown in Table 4 with corporate income and business taxes.

In general, states which are regressive without corporate and business taxes are even more regressive when these taxes are included. The Spearman's rank correlation coefficient between the orders implied by the two different progressivity measures is 0.94.

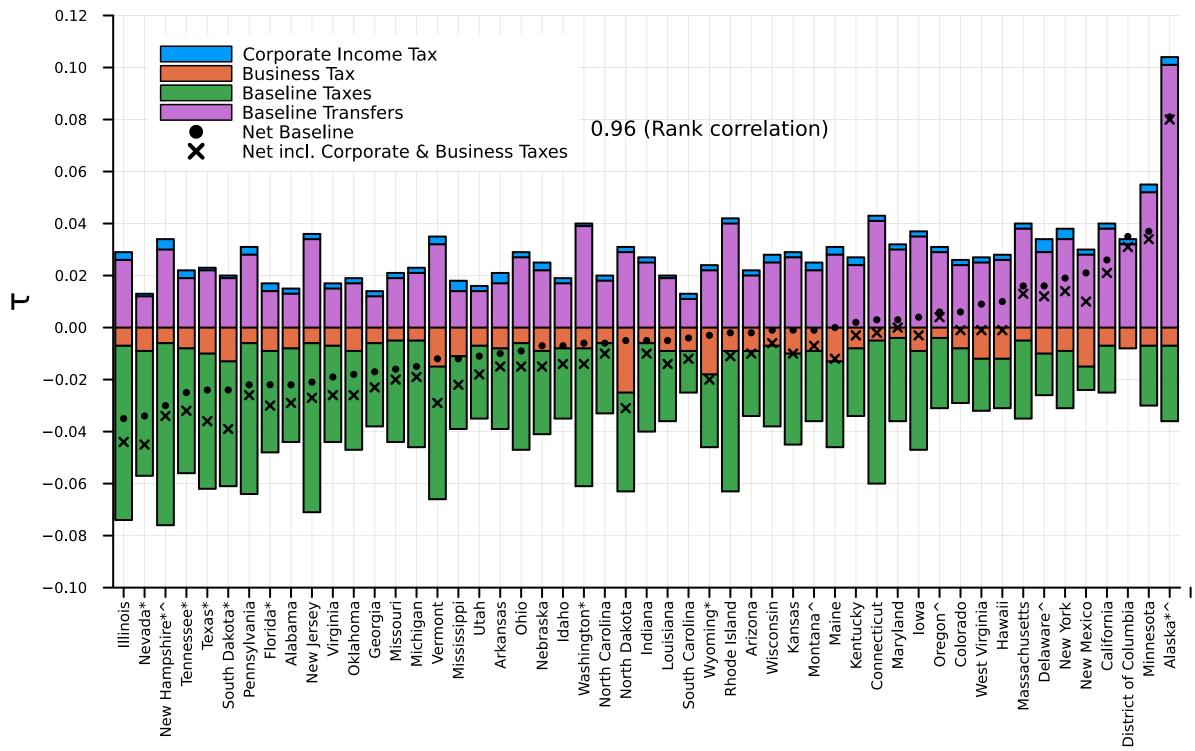

Figure 25: State τ^s decomposition. The plot shows estimates for progressivity induced by each of the state level taxes and transfers indicated in the legend, considering one tax at a time, using household weights constructed as described in appendix I. The black dots report overall state progressivity as reported in Figures 16 and 17. Estimates are for 2015/2016.

JF: Let's add some text to remind/explain that nonlinearity in the estimation can lead to unintuitive outcomes - see Alaska. Readers will ask: "Why is the sum of the CI and B Tax negative but net baseline lower than net new?"

5 Extension 2: Including Federal and State and Local Spending

In this section, we explore the sensitivity of our results to a more comprehensive notion of transfers. In this ″broad″ transfer measure, we include all state and local spending on public goods and services.

We present these calculations as an extension, rather than part of our baseline, because accurately modeling how public spending on each separate component is valued by different households is extremely challenging, and beyond the scope of this paper. Two main complications arise. The first one is that when goods or services are publicly-provided, high and low income households are effectively forced to consume them in equal amounts. For low income households, who are forced to over-consume, the private value of public spending on education, healthcare and other government-provided services likely falls short of the dollar cost of that spending. Thus, counting spending on public goods and services as a transfer may exaggerate the value of public income support that low income households receive. The second issue is that there are positive externalities associated with many publicly-provided goods and services. For example, higher education spending likely reduces crime and unemployment, and thus benefits all households, not just those with school-age children.[39]

With these caveats in mind, to make some progress we assess the value of government consumption to households based on their production costs. For consistency, in this broad measure of progressivity, we also value Medicaid and Medicare receipt to enrollees at 100% of the amount spent.[40] We proceed incrementally, and thus in this "broad transfer" extension we also include the state corporate and business taxes discussed in the previous section.please confirm that is true

Specifically, to construct the broad transfer measure, we collect data on federal spending from NIPA and data on state and local spending from the Census of State and Local Governments. We allocate federal, state and local spending on elementary and secondary education in proportion to the number of school-age children in the household (in the state, for state and local expenditures). Finally, we allocate all remaining federal, state and local spending in a lump-sum fashion across all households (in the state, for state and local expenditures).[41] We subtract

[39]This logic may also apply to Medicaid spending and to food stamps, though food stamps are likely closer substitutes to cash than is public health insurance or free schooling.

[40]In Appendix K we report results for an intermediate case in which Medicaid and Medicare receipts to enrollees are valued at 100% of the amount spent, but in which we do not include state and local government consumption as part of our transfer measure.

[41]We allocate tertiary education lump-sum because the ASEC does not report whether adults in the households have kids enrolled in college.

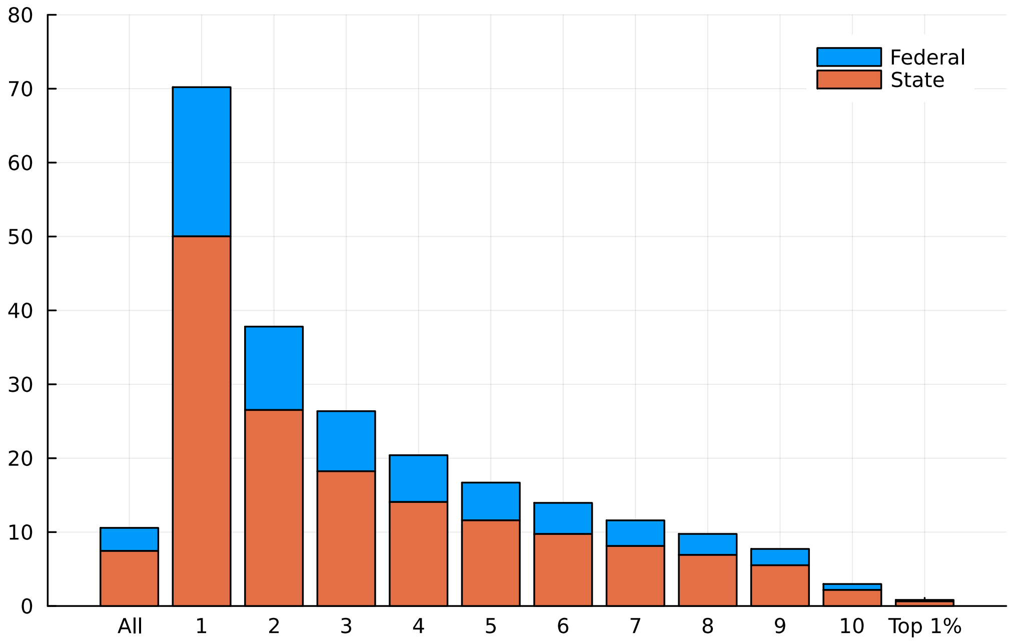

Figure 26: Average spending rates (as a share of income) for 2015/2016. See notes to Figure 1.

from these expenditures revenues from charges that state and local government obtain in exchange of providing services (e.g., airport fees, highway tolls). Appendix N contains a more detailed description of our calculations.

Figure 1 plots average federal and state spending rates, as a share of income, by income decile. Excluding Medicare, Federal spending is small relative to state-level expenditures and mostly made of spending on defense and public safety.must decide whether this plot should include Medicare at full cost. State-level spending (excluding Medicaid) is dominated by education. Overall, on average spending on publicly-provided services accounts for 11% of household income but, by nature of the imputation, is strongly progressive.

Figure 27 shows that once this broad measure of transfers is incorporated into our estimates, the net tax rate across states falls by roughly half, from a US average of XYZ to XYZ.Add numbers. We should probably split transfer bars into narrow and the rest. Finally, Figure 28 reports our state-level measures of progressivity τ^*, and its decomposition. Overall, once this broad measure of transfers is taken into account, τ^* increases sharply, on average by XYZ ppts.Discuss format of this plot

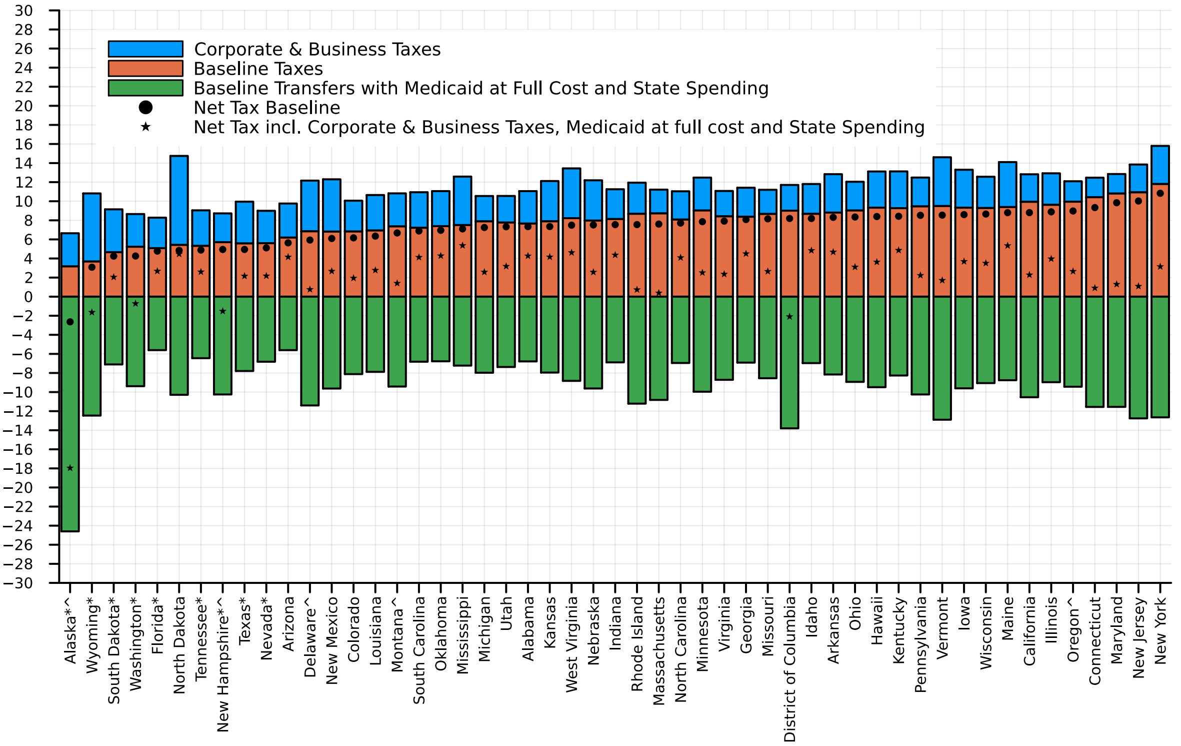

Figure 27: Average tax and transfer rates by state, including state spending as transfers. Baseline taxes includes income, excise, sales and property taxes. Corporate & Business Taxes include corporate income and business taxes. Transfers include baseline transfers, Medicaid at full cost and state spending on public goods and services. ASEC baseline sample, 2015/2016.

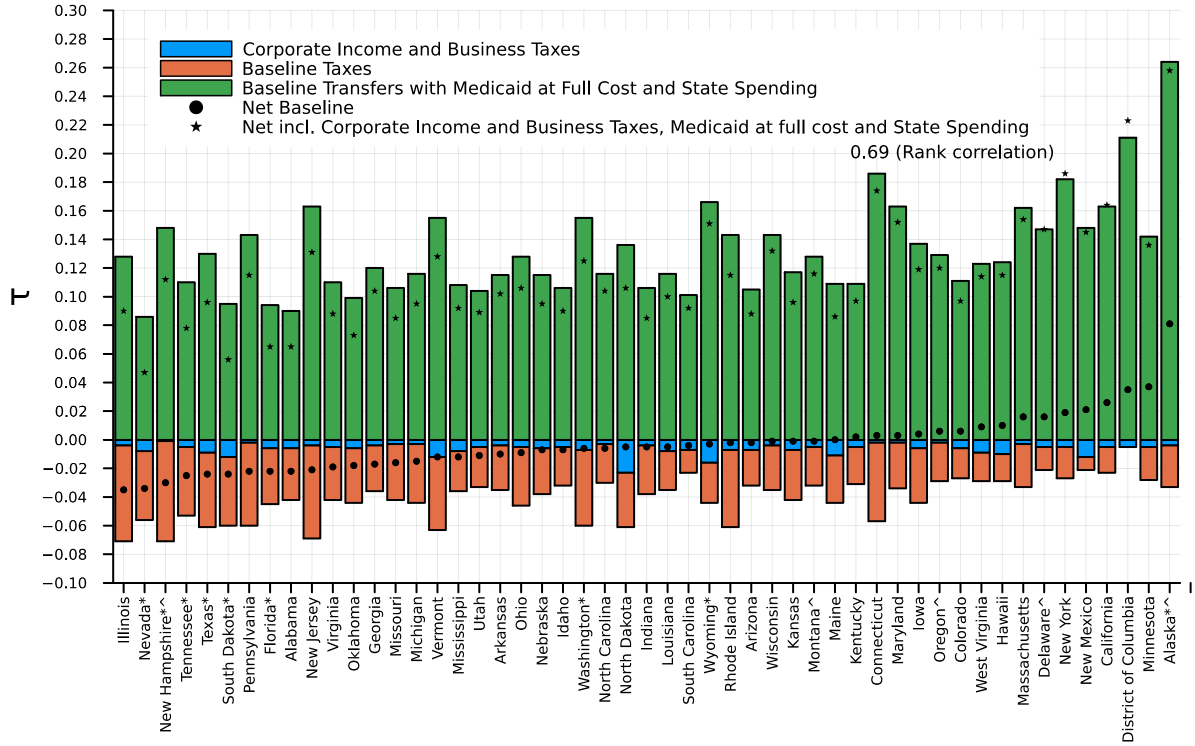

Figure 28: State τ^s decomposition. The plot shows estimates for progressivity induced by each of the state level taxes and transfers indicated in the legend, considering one tax at a time, using household weights constructed as described in Appendix I. The black dots report overall state progressivity as reported in Figures 16 and 17. Estimates are for 2015/2016.

6 Conclusion (to be completed)

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Appendix

The appendix is organized as follows. Section A provides an overview on state and local tax collections. Section B explains for which ASEC households we use income and tax information from the IRS SOI and Section C presents summary statistics from our ASEC sample. Sections D, H, F, M, E, and L contain detailed explanations on the measurement of transfers, property taxes, consumption taxes, and corporate taxes, respectively. Section I documents the methodology we use to align state income distributions before estimating state specific tax and transfer progressivity.

A State and Local Taxes

A.1 Size and Composition

Figure 29 shows all revenues of the state and local governments within each U.S. state and the District of Columbia in 2016 as shares of state GDP.[42] Except in Alaska (where oil related revenues, recorded in ”Miscellaneous”, are substantial), tax collections are the by far largest source of revenue in every state. Expressed as a share of state GDP, they range from 5.5% (in Alaska) to 11.6% in New York, Maine and Vermont.

[42] Taxes include: property taxes, sales and excise taxes, individual income taxes, corporate income taxes, and other other taxes (such as motor vehicle license taxes, death and gift taxes, documentary and stock transfer taxes as well as severance taxes). Miscellaneous includes revenues from the sale of public assets, earnings distributions by publicly owned corporations, fines and forfeits, privilege royalties (primarily related to oil, gas and mineral extractions) and lottery revenues. Current Charges includes charges from schools, universities, hospitals, highways, parks and recreation, among others. See Census Bureau (2006) for details.

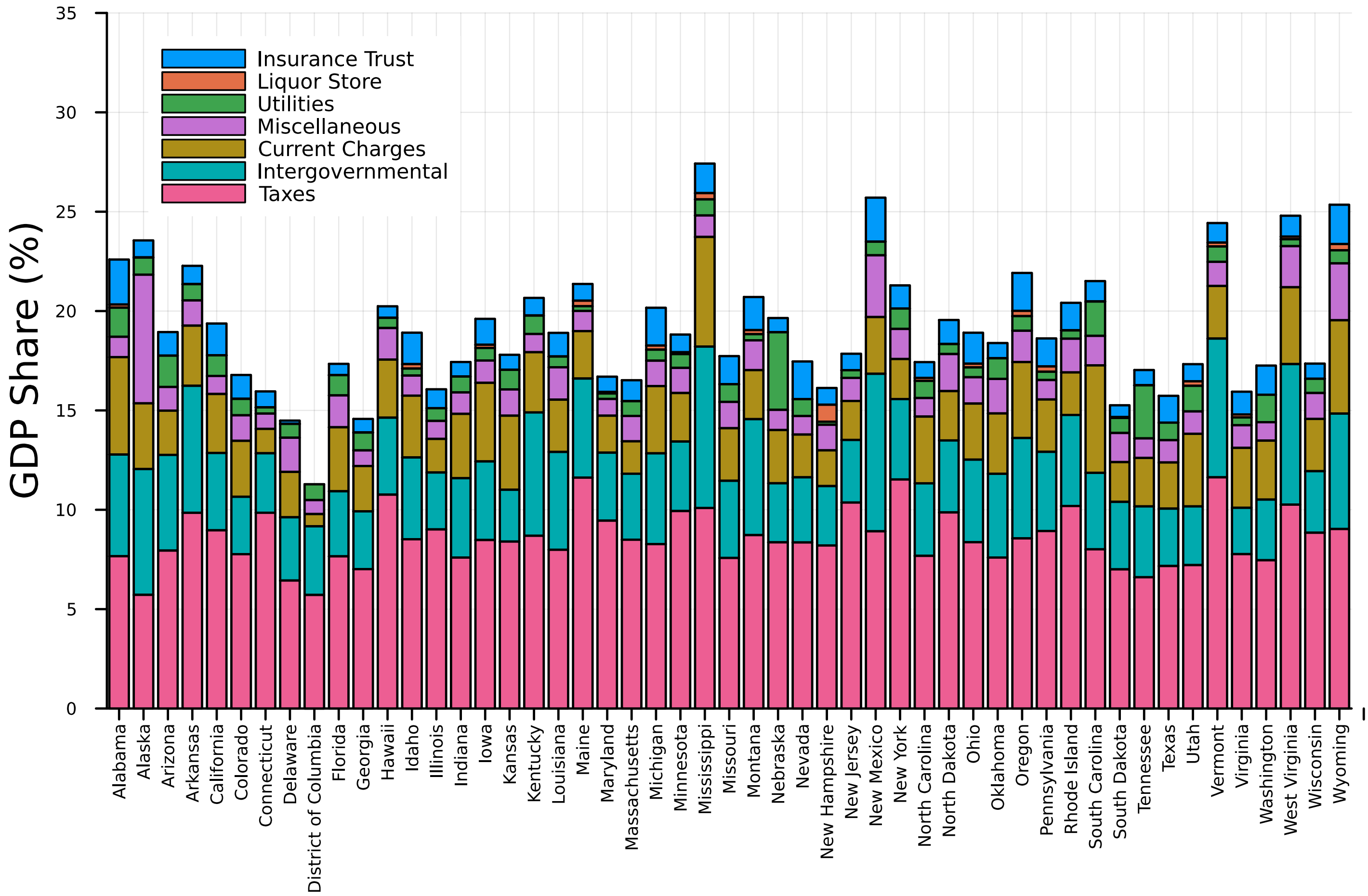

Figure 29: State and Local Total Revenues as Shares of State GDP (2016). Source: Census of State and Local Governments and Bureau of Regional Analysis.

A.2 State vs. Local Taxes

In Figure 30, we break total state and local tax collections in 2016 into granular categories and plot them separately for state governments (top panel) and local governments (bottom panel).

- Property taxes represent about 3% of state GDP, on average. Except in Vermont, they are almost exclusively levied by local governments.
- Sales taxes are collected in most states, and excise taxes are collected in all states. They are predominantly collected at the state level, and are the most important source of tax revenue for state governments, constituting about 3% of state GDP.
- Individual income is untaxed in a few states (Alaska, Florida, Nevada, South Dakota, Texas, Tennessee, Washington, Wyoming). In states where income is taxed, income taxes represent about 2% of GDP, on average. Income is generally taxed at the state level, but there are also local income taxes in some states.[43]
- Corporate income taxes are a minor source of tax revenue for all state and local governments, representing about 0.2% of state GDP. Corporate income is generally taxed at the state level, though New York does have local corporate income taxes.

[43] See Appendix D for more details on local income taxes.

- Other taxes are significant only in a handful of states (Alaska, Delaware, Montana, North Dakota, Wyoming). They typically reflect taxes collected from entities and activities related to the extraction of natural resources (such as oil, gas and minerals).

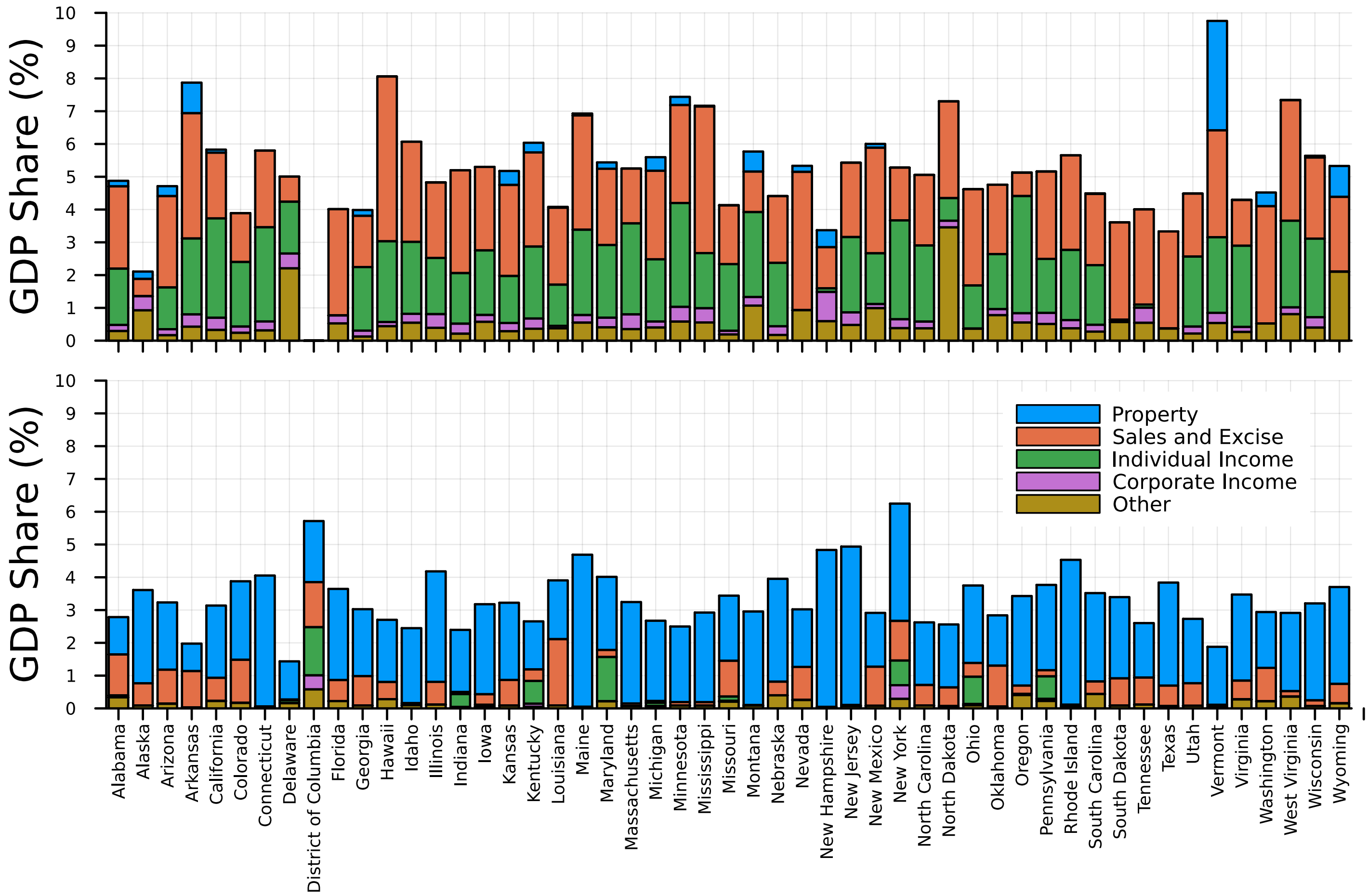

Figure 30: Top Panel: State Tax Revenues as Shares of State GDP (2016). Bottom Panel: Local Tax Revenues as Shares of State GDP (2016). Source: Census of State and Local Governments and Bureau of Regional Analysis.

A.3 Tax Collections from Households vs. Businesses

State and local governments collect taxes from households and businesses. According to Ernst and Young (2016), business tax collections include property taxes, sales taxes, excise taxes (including public utilities and insurance), corporate income taxes, unemployment insurance taxes, individual income taxes on business income as well as license and other taxes. Using data for 2016 from the same source, we split total state and local tax collections shown at the bottom of Figure 29 (red) in those collected from households (green) and businesses (orange) in Figure 31.

On average, the business share is 46%, i.e. about half of all taxes were collected from businesses. However, cross state variation is sizable with shares ranging from 30% to 75%. In general, the share is highest (above 60%) in states with activity in resource extraction (Alaska, North Dakota, Texas and Wyoming) and lowest (below 40%) in California, Maryland, Michigan, North Carolina and Oregon.

We account for these differences in business tax collections in our measurement of state tax and transfer progressivity by assigning them to households using clear assumptions on their incidence. See section 4.2 and appendix M.

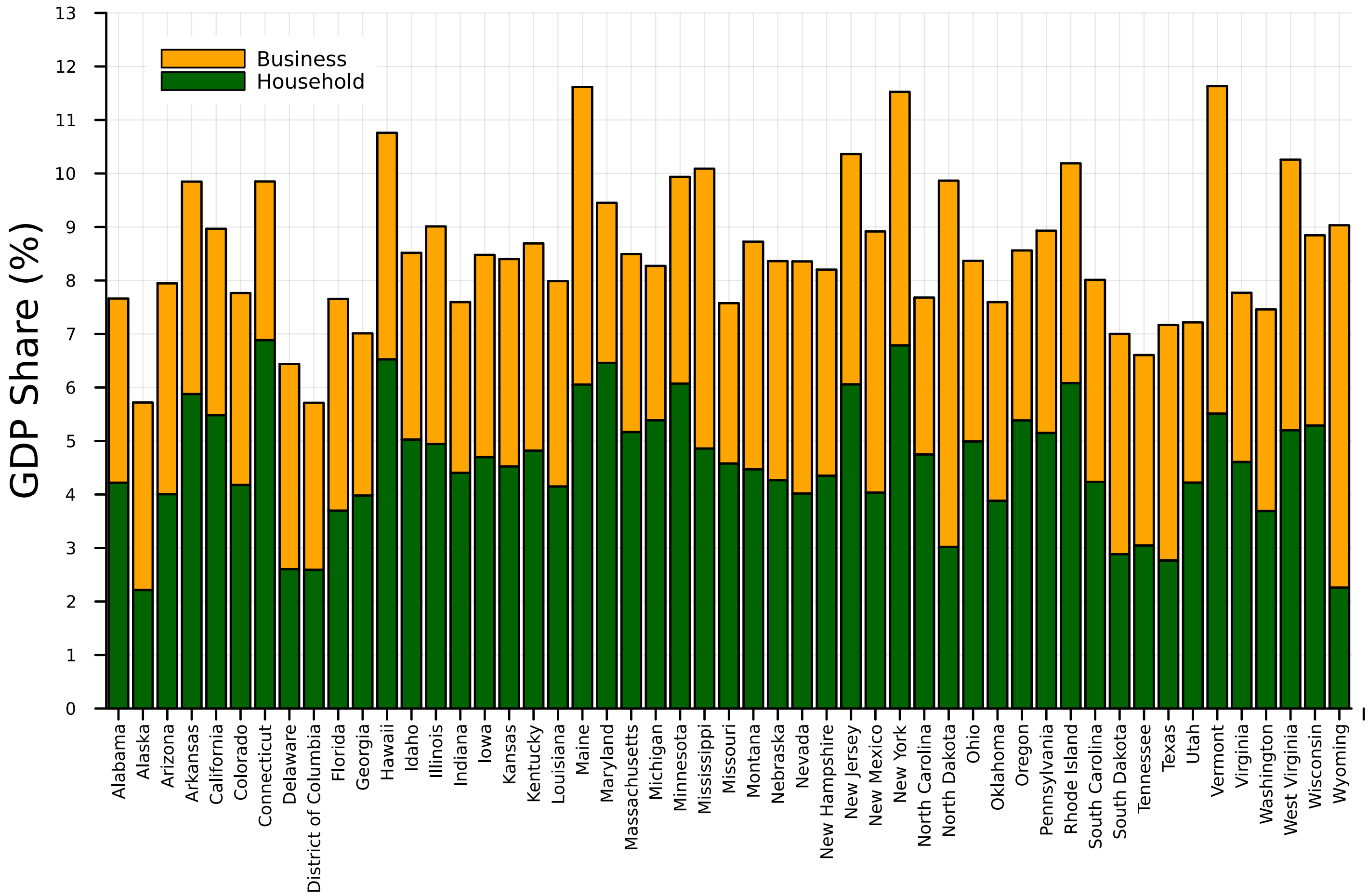

Figure 31: State and Local Total Tax Revenues from Businesses and Households as Shares of State GDP (2016). Source: Census of State and Local Governments, Bureau of Regional Analysis and Ernst and Young (2016).

B Replacing Incomes and Taxes of High-Income ASEC Households with SOI Data

B.1 Census Bureau Modifications of ASEC Incomes and Income Taxes

To protect the confidentiality of respondents, the Census Bureau applies disclosure avoidance procedures before making the ASEC micro data available to the public. One of these procedures modifies information on high-income amounts reported by survey participants. During our sample years, the Census Bureau used two different methods to implement these income modifications; Average Replacement Values (2005, 2006 and 2010) and Rank Proximity Swapping (2011, 2015 and 2016).[44] The Average Replacement Value method replaces self-reported incomes which exceed a given threshold value. However, unlike traditional topcoding, it does not set them equal to this threshold but replaces them with the mean income reported by respondents of similar observable characteristics (age, race, gender, etc). Rank Proximity Swapping, on the other hand, also replaces all reported incomes above a given threshold but swaps them among respondents within a bounded interval. However, these methods are applied only to a subset of all self-reported ASEC income categories while others are subject to traditional topcoding. Finally, the ASEC federal and state income tax variables imputed by the Census Bureau tax model are topcoded at $99,999 in

[44]For more details, see this Census Bureau document https://www2.census.gov/programs-surveys/demo/datasets/income-poverty/time-series/data-extracts/pu-swaptopcodes-readme.docx and the summary compiled by IPUMS: https://cps.ipums.org/cps/topcodes_tables.shtml.

years 2005 and 2006 but unrestricted in later sample years.

Due to these disclosure avoidance procedures, the publicly available ASEC micro data have two major limitations regarding the measurement of tax progressivity, in particular with respect to cross-state differences. First, the federal and state income tax variables in 2005 and 2006 understate the taxes paid by high-income households. As a result, federal progressivity is underestimated and states with high income taxes for top earners might appear less progressive than they actually are. Second, as the Average Replacement Value and Rank Proximity Swapping methods do not use geographic variables in assigning replaced values, they fail to accurately capture cross-state differences in the top tail of states' income distributions. Hence, estimates of tax and transfer progressivity partly reflect these pre-tax income adjustments rather then genuine policy differences.

While these procedures make it impossible to determine self-reported incomes (and imputed taxes) in the ASEC micro data, they still allow to compute the lower bound of each household's self-reported income. In other words, we can identify households with members who self-reported total incomes at least equal to or larger than a given Dollar amount. To see this, let ASEC household total income be denoted as

$$y_i = \sum_{j=1}^{J} \sum_{k=1}^{K} y_{j,k} \tag{4}$$

where i denotes households, j indexes household i's members, k are distinct income categories and $y_{j,k}$ is the by-person income value included in the public version of the ASEC dataset. Note that, for income variables subject to Average Replacement Value and Rank Proximity Swapping

$$y_{j,k} = \begin{cases} y^*_{j,k} & \text{if } y^*_{j,k} < \overline{y}_k \\ \tilde{y}_{j,k} & \text{if } y^*_{j,k} \geq \overline{y}_k \end{cases} \tag{5}$$

where $y^*_{j,k}$ is the value reported by the respondent, $\tilde{y}_{j,k}$ is the modified value of $y^*_{j,k}$ and $\overline{y}_k$ is the replacement threshold. For income categories subject to traditional topcoding

$$y_{j,k} = \begin{cases} y^*_{j,k} & \text{if } y^*_{j,k} < \overline{Y}_k \\ \overline{Y}_k & \text{if } y^*_{j,k} \geq \overline{Y}_k \end{cases} \tag{6}$$

where $\overline{Y}_k$ is the topcode of income category k.

Using information on $y_{j,k}$, $\overline{y}_k$ and $\overline{Y}_k$, we can compute the lower bound of total household income as

$$\underline{y}_i = \sum_{j=1}^{J} \left\{ \underbrace{\sum_{k=1}^{\underline{K}} y_{j,k} | y_{j,k} < \overline{y}_k}_{\text{unmodified income categories}} + \underbrace{\sum_{k=1}^{\overline{K}} \overline{y}_k | y_{j,k} \geq \overline{y}_k}_{\text{modified income categories}} + \underbrace{\sum_{k=1}^{\widehat{K}} y_{j,k}}_{\text{topcoded income categories}} \right\} \leq y_i \tag{7}$$

where $\underline{K} + \overline{K} + \widehat{K} = K$.

B.2 Merging SOI Incomes and Income Taxes into the ASEC dataset

To address the limitations in the ASEC data caused by the income modifications described above, we turn to state-level data published by the Statistics of Income (SOI) program of the Internal Revenue Service (IRS). Drawing from information reported on 1040 Forms, it provides averages of individual total incomes and taxes paid for different bins of adjusted gross income (AGI) in each state.[45] Total income is the sum of all income items reported on Form 1040, before adjustments, and is broken down into its granular components. Importantly, it includes capital gains which are unavailable in ASEC and are concentrated among households with high incomes.[46] The SOI data also provide the employee portion of all FICA taxes and we impute the employer portion as described in section 2.1.

Moreover, from itemized deductions, the SOI provides data on property taxes as well as state and local income taxes. Notably, the SOI data show that high-income households residing in states without income taxes still pay some taxes as they earn income in states where income is taxable. Finally, recall our measure of ASEC pre-government income is the sum of income from wages and salaries, self-employment, farming, interest, dividends, rents, private transfers and other income. The SOI data allow to construct a corresponding income measure by subtracting unemployment compensation and taxable social security benefits from total income and add the employer FICA contribution.[47]

We use the SOI data to replace the incomes and taxes of ASEC households which meet at least one of two conditions:

1. The lower bound on household self-reported pre-government income, $\underline{y}_i$, is equal to \$200,000.
2. At least one of the income tax variables is at the topcode for at least one household member.

We set the lower bound equal to \$200,000 for two reasons. First, even though the SOI AGI bins change between years, we have information on incomes above \$200,000 throughout our sample years; "\$200,000 or more" is the highest AGI bin for 2005 and 2006 while the bins in the other sample years (2010, 2011, 2015 and 2016) are "\$200,000 under \$500,000", "\$500,000 under \$1,000,000", and "\$1,000,000 or more". In these years, we rank ASEC households which meet at least one of the two conditions above by their incomes and then replace their incomes and taxes by drawing from the three top SOI income bins in proportion to their respective shares of all tax returns. In this way, we retain the ordinal ranking provided by the Census Bureau's disclosure avoidance procedures when replacing with SOI information. Second, within the \$200,000 AGI bins, no less than 93.3% of tax filers itemized deductions instead of choosing the standard deduction. Thus, this income threshold gives us reasonable measures of state and local income taxes as well as property taxes.[48]

For the entire dataset in 2015/2016, the share of SOI replaced households is 5.4%. For reference, the share of tax returns with AGI above \$200,000 is 4.6%.[49] We report the total and by income decile replaced share in appendix C.2, tables 6 (for our sample) and table 7 (for the entire ASEC dataset).

[45] See "SOI tax stats - Historic Table 2": https://www.irs.gov/statistics/soi-tax-stats-historic-table-2

[46] The ASEC dataset includes imputed variables on capital gains and losses only for years 1992 to 2008.

[47] Note that, other than unemployment compensation, the SOI data do not provide any of the transfer categories available in ASEC (see table 2). Hence, we do not replace transfer variables.

[48] This share of itemizers declined substantially from 2018, i.e. after our last sample year, as the Tax Cut and Jobs Act (TCJA) of 2017 capped the state and local tax (SALT) deduction at \$10,000.

[49] In 2005/2006 and 2010/2011 these shares are 2.7% (2.8%) and 3.5% (3.1%). Note that AGI is not the same as our concept of gross income (AGI is slightly lower because it includes adjustments).

B.3 Taxes Paid by High Income Households

Figure 32 plots average tax rates by state for households in the $500,000-$1m AGI bucket in the SOI tables. This plot is constructed directly from the IRS-SOI tables, and does not include sales, excise or corporate income taxes. Note the wide variation in effective state income tax rates faced by these high income households, which reflects cross-state differences in the level and progressivity of statutory rates. Nine of the ten lowest tax states are those which do not have a state income tax. Note also that high income households in states without state income taxes tend to pay a slightly larger share of income in federal taxes, reflecting their inability to deduct state taxes on federal returns.

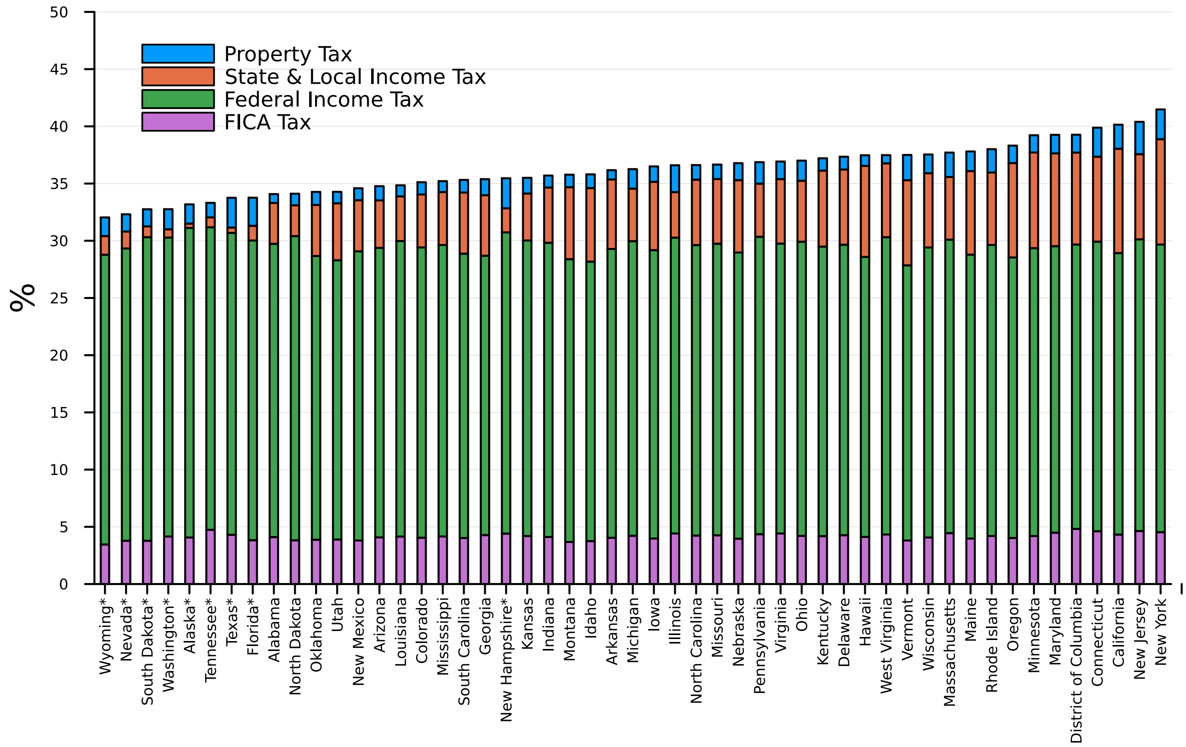

Figure 32: Taxes and transfers for households with income between $500,000 and $1,000,000 by state. Source: IRS SOI 2016. States without income tax are marked with an asterisk.

C Summary statistics

C.1 Sample Size by State

As our focus is on cross-state differences in tax and transfer progressivity, we require a dataset which provides us with a reasonable number of households after applying our sample selection conditions. Figure 33 shows that, for all of our sample years, we have no less than 500 households in each state in our sample (without applying ASEC household weights).

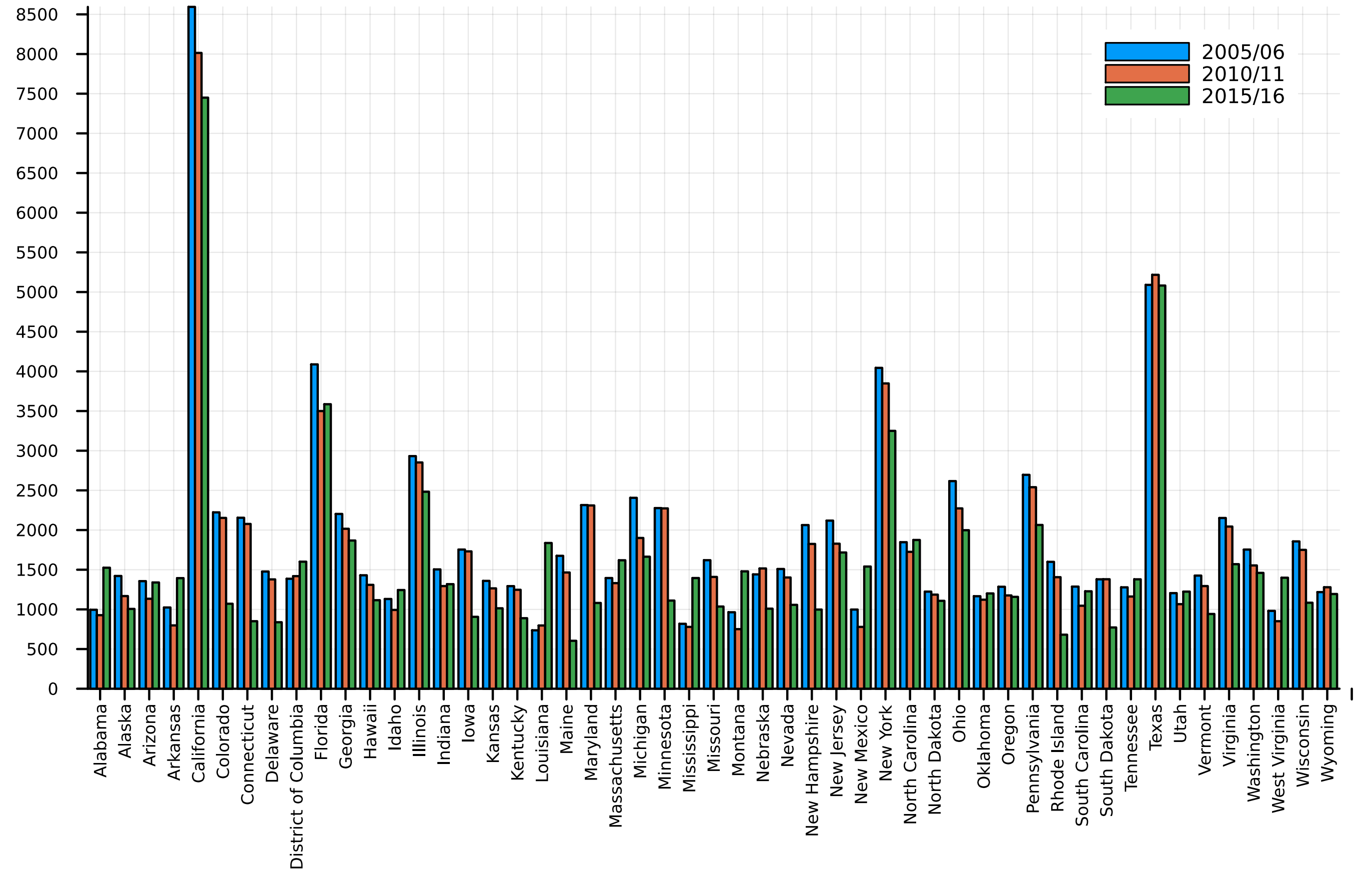

Figure 33: Households by state in the ASEC baseline sample. This sample selects households with heads aged between 25 and 60 and one spouse having at least part-time at minimum-wage labor earnings.

C.2 Distributions of Income, Taxes and Transfers

C.2.1 Our ASEC Sample

	All	1	2	3	4	5	6	7	8	9	10	Top 1%
Pre-Government Income (ASEC, self-reported, SOI)	119,534	18,691	33,060	45,598	58,425	72,598	88,373	107,293	131,631	169,751	469,776	1,969,520
Wage and Salary Income (ASEC, self-reported, SOI)	93,927	16,657	30,722	42,193	55,409	67,638	83,660	100,865	123,498	157,214	261,389	701,151
<= 0 (%)	0	0	0	0	0	0	0	0	0	0	0	0
SOI Replaced (%)	8	0	0	0	0	0	0	0	0	0	83	100
Total Transfers	6,000	12,622	8,889	7,505	5,951	5,251	4,678	3,988	3,862	3,598	3,660	3,178
Federal Transfers	3,818	8,218	5,548	4,637	3,695	3,226	2,955	2,530	2,526	2,389	2,454	2,037
School Lunch (ASEC, self-reported)	130	329	245	181	129	102	87	67	60	52	48	65
Veterans' Benefits (ASEC, self-reported)	258	253	196	220	242	302	259	288	318	246	252	118
Survivors' Benefits (ASEC, self-reported)	185	220	85	152	157	127	142	165	268	235	301	192
Disability Benefits (ASEC, self-reported)	215	290	226	222	177	193	219	172	228	191	229	76
SS SI and DI Benefits (recipients age < 62; ASEC, self-reported)	478	1,025	750	639	527	446	407	310	243	264	174	90
SS OA Benefits (recipients age >= 62; ASEC, self-reported)	422	517	475	428	433	387	379	358	371	436	432	484
SNAP (CBO imputed)	401	1,657	870	580	330	200	135	88	66	45	36	46
SSI (CBO imputed)	205	557	362	305	202	164	127	100	82	72	84	88
Housing Assistance (CBO imputed)	109	688	232	103	30	16	6	6	3	3	1	3
Medicare (imputed, cash value)	666	1,089	904	798	687	603	625	506	456	476	521	483
State Transfers	857	1,621	1,229	1,093	877	808	711	618	559	540	518	420
Unemployment Insurance (ASEC, self-reported)	187	307	213	198	196	171	174	153	145	171	145	75
Workers' Compensation (ASEC, self-reported)	83	120	101	120	72	93	82	84	56	56	49	12
Alaska PFD (ASEC, self-reported, imputed)	11	5	7	9	11	13	10	14	12	15	11	6
Joint Federal-State Transfers	1,325	2,783	2,112	1,775	1,379	1,217	1,013	840	777	669	688	721
TANF (ASEC, self-reported)	31	101	46	33	20	30	25	18	16	7	12	33
Medicaid (imputed, cash value)	1,294	2,682	2,066	1,742	1,359	1,187	987	822	761	662	677	687
Amount cond. on recipiency	3,053	4,105	3,806	3,592	3,188	2,832	2,603	2,334	2,287	2,114	2,010	1,929
Recipients (% of persons)	30	67	56	46	35	29	23	19	16	14	15	18
Income Taxes (imputed, ASEC, SOI, CSLG, BEA)	22,759	-2,145	-66	2,466	4,800	7,306	10,092	15,876	23,159	32,882	133,185	674,957
Federal (ASEC, SOI)	18,104	-2,250	-597	1,486	3,395	5,457	7,653	12,678	19,131	27,346	106,703	536,448
State & Local (ASEC, SOI, CSLG, BEA)	4,656	105	531	980	1,405	1,850	2,438	3,197	4,028	5,536	26,482	138,509
FICA (employee, employer, self-employment; ASEC, SOI, imputed)	12,419	2,626	4,648	6,384	8,174	10,097	12,320	14,842	18,036	22,109	24,956	41,647
Consumption Taxes (imputed, CEX, BEA, CSLG)	3,259	1,782	2,084	2,319	2,577	2,877	3,172	3,504	3,903	4,419	5,955	11,903
Federal (Excise)	448	293	344	371	400	432	463	496	517	538	621	964
State	2,812	1,489	1,740	1,948	2,177	2,445	2,710	3,008	3,386	3,881	5,333	10,939
Sales	1,838	864	1,019	1,159	1,327	1,516	1,712	1,934	2,247	2,670	3,937	8,869
Excise	973	625	722	789	850	929	998	1,074	1,139	1,211	1,397	2,070
Property Taxes (imputed, ACS, SOI)	2,709	1,480	1,580	1,698	1,823	1,958	2,141	2,416	2,658	3,230	8,109	19,717
Owners	3,272	1,938	1,921	1,970	2,054	2,174	2,333	2,608	2,837	3,437	8,539	20,750
Renters	1,717	1,209	1,309	1,413	1,530	1,599	1,721	1,868	2,035	2,282	5,717	13,539
Corporate Income Taxes (imputed)	3,923	32	57	82	131	198	528	1,915	2,629	3,972	29,659	174,186
Federal (all profits + all labor)	3,343	27	49	70	111	163	434	1,676	2,242	3,365	25,278	148,741
State (all profits + in state labor)	579	5	8	12	20	35	93	239	387	607	4,381	25,444
State Business Taxes (imputed, ASEC, CEX, BEA, EY)	3,396	900	1,345	1,744	2,126	2,563	3,021	3,579	4,306	5,338	9,035	24,433
Labor	2,535	466	860	1,176	1,544	1,865	2,296	2,761	3,363	4,191	6,829	17,953
Consumers	639	345	390	432	478	525	577	641	740	871	1,388	3,759
Property	222	89	95	136	104	173	147	177	203	276	818	2,721
Public Spending (imputed, BEA, CSLG)	12,640	13,123	12,500	12,024	11,924	12,125	12,334	12,436	12,843	13,114	13,983	16,233
Federal (all households)	3,735	3,774	3,732	3,708	3,702	3,709	3,720	3,726	3,744	3,750	3,783	3,853
State (in state households)	8,906	9,349	8,768	8,316	8,222	8,415	8,614	8,710	9,098	9,364	10,200	12,380
Joint Filers (ASEC, %)	58	30	36	41	47	55	64	69	75	79	83	84
HH Head Filers (ASEC, %)	11	28	20	16	13	11	8	7	5	4	3	4
Single Filers (ASEC, %)	31	42	44	43	40	34	28	25	20	17	14	11
HH owners (ASEC, %)	64	37	44	51	56	62	69	74	78	82	85	86
HH size (ASEC)	2.9	2.5	2.5	2.6	2.7	2.8	2.9	3	3.1	3.2	3.3	3.4
HH head age (ASEC)	43.7	42.6	42.7	43	43.1	43.4	43.4	43.8	44	45.1	46.1	46.4
HH head age > 60 (ASEC, %)	2	3	2	2	2	2	2	2	2	2	2	3
HH at least one member age > 65 (ASEC, %)	3	4	4	3	3	3	3	3	3	4	4	5
N, unweighted	80,315	8,063	8,062	7,976	7,973	8,121	8,014	8,126	8,111	8,008	7,860	761
N, ASEC weights	137,302,140	13,729,648	13,729,626	13,729,520	13,731,321	13,730,154	13,730,375	13,729,271	13,731,304	13,730,061	13,730,508	1,376,159

Table 6: Distribution of income, taxes, and transfers in our baseline sample, 2015/2016. Numbers have been computed using ASEC household weights. This sample selects ASEC households with heads aged between 25 and 60 and one spouse earning at least $7,250 (minimum wage part-time work).

The column labelled "All" reports average income and tax and transfer values for the entire sample. The columns labelled "1" through "10" correspond to deciles of households ranked by household pre-government income, where each decile bin contains about the same (weighted) number of households. The column labelled "Top 1%" refers to the one percent of households with the highest incomes. All variables are in current $ or %, except "HH size" which reports number of persons, "HH head age" which is in years, "N, unweighted" and "N, ASEC weights" which report number of households. "SOI Replaced" is the share of ASEC households in each decile for whom income and tax variables are imputed using IRS-SOI data. Local income taxes are included in state income taxes for SOI replaced households and households residing in Indiana, Maryland or New York.

C.2.2 Entire ASEC Dataset

	All	1	2	3	4	5	6	7	8	9	10	Top 1%
Pre-Government Income (ASEC, self-reported, SOI)	81,607	-85	264	8,960	25,244	40,139	56,559	76,042	100,824	138,175	369,883	1,534,143
Wage and Salary Income (ASEC, self-reported, SOI)	63,142	6	50	5,895	21,352	36,006	51,987	69,824	92,699	127,153	226,433	589,230
<= 0 (%)	5	54	0	0	0	0	0	0	0	0	0	0
SOI Replaced (%)	5	0	0	0	0	0	0	0	0	0	54	100
Total Transfers	15,701	31,996	34,357	26,261	15,882	12,003	9,470	7,986	7,234	5,956	5,868	6,136
Federal Transfers	13,256	27,516	32,116	23,005	12,449	9,177	7,194	6,126	5,675	4,617	4,683	5,009
School Lunch (ASEC, self-reported)	99	79	35	149	211	158	109	86	64	54	43	61
Veterans' Benefits (ASEC, self-reported)	458	777	1,018	614	301	310	288	341	359	309	267	426
Survivors' Benefits (ASEC, self-reported)	403	393	984	745	328	231	187	212	358	268	322	244
Disability Benefits (ASEC, self-reported)	289	451	497	374	257	205	267	216	194	235	190	66
SS SI and DI Benefits (recipients age < 62; ASEC, self-reported)	772	2,172	1,199	1,049	841	692	510	407	390	260	199	138
SS OA Benefits (recipients age >= 62; ASEC, self-reported)	5,211	9,400	15,418	9,916	4,258	3,053	2,476	2,185	2,013	1,631	1,761	2,115
SNAP (CBO imputed)	533	1,202	558	1,154	1,054	606	342	194	109	68	46	50
SSI (CBO imputed)	435	1,661	632	568	451	327	246	173	112	91	86	71
Housing Assistance (CBO imputed)	296	1,293	566	619	299	125	35	13	7	3	2	2
Medicare (imputed, cash value)	3,890	8,363	10,398	6,635	3,193	2,467	1,946	1,666	1,569	1,270	1,399	1,446
State Transfers	915	1,470	815	1,199	1,231	1,064	884	734	667	570	512	418
Unemployment Insurance (ASEC, self-reported)	153	71	49	199	195	196	177	156	178	164	145	70
Workers' Compensation (ASEC, self-reported)	91	112	146	117	85	103	92	74	85	51	50	19
Alaska PFD (ASEC, self-reported, imputed)	9	3	4	5	7	8	10	12	12	12	11	9
Joint Federal-State Transfers	1,531	3,011	1,426	2,058	2,201	1,762	1,392	1,126	892	770	674	710
TANF (ASEC, self-reported)	49	142	55	104	62	31	25	27	19	15	9	18
Medicaid (imputed, cash value)	1,482	2,868	1,371	1,953	2,140	1,730	1,367	1,099	873	755	665	692
Amount cond. on recipiency	3,812	5,999	5,494	4,536	4,138	3,762	3,364	2,871	2,589	2,359	2,172	1,987
Recipients (% of persons)	32	52	29	51	55	46	35	27	20	16	14	17
Income Taxes (imputed, ASEC, SOI, CSLG, BEA)	15,813	341	1,375	714	146	2,467	5,284	8,611	14,434	25,750	98,987	515,087
Federal (ASEC, SOI)	12,636	301	1,214	520	-255	1,618	3,882	6,593	11,428	21,490	79,549	413,619
State & Local (ASEC, SOI, CSLG, BEA)	3,177	40	161	194	401	849	1,402	2,018	3,006	4,260	19,438	101,468
FICA (employee, employer, self-employment; ASEC, SOI, imputed)	8,412	1	8	940	3,302	5,418	7,736	10,398	13,713	18,461	24,139	37,286
Consumption Taxes (imputed, CEX, BEA, CSLG)	2,626	1,167	1,155	1,426	1,951	2,214	2,536	2,943	3,391	4,011	5,461	10,330
Federal (Excise)	376	203	202	240	321	360	396	439	485	521	594	872
State	2,250	964	953	1,187	1,630	1,854	2,140	2,504	2,906	3,489	4,866	9,458
Sales	1,437	548	532	673	950	1,092	1,297	1,562	1,857	2,333	3,527	7,529
Excise	812	417	421	514	680	762	843	942	1,049	1,156	1,339	1,929
Property Taxes (imputed, ACS, SOI)	2,359	1,397	1,740	1,726	1,615	1,691	1,833	2,016	2,339	2,786	6,448	17,033
Owners	2,846	1,768	1,963	2,119	2,047	1,999	2,080	2,231	2,543	2,975	6,836	17,885
Renters	1,515	1,018	1,179	1,216	1,239	1,364	1,501	1,623	1,791	2,083	4,410	12,173
Corporate Income Taxes (imputed)	2,958	4	44	619	471	463	447	623	1,922	3,394	21,582	136,047
Federal (all profits + all labor)	2,520	3	37	527	401	393	380	517	1,664	2,892	18,374	116,498
State (all profits + in state labor)	438	1	7	92	70	70	67	106	258	502	3,208	19,548
State Business Taxes (imputed, ASEC, CEX, BEA, EY)	2,382	249	245	492	1,056	1,528	2,031	2,634	3,339	4,437	7,807	20,724
Labor	1,706	0	1	164	596	1,008	1,445	1,929	2,533	3,438	5,946	15,368
Consumers	518	248	243	291	367	413	470	538	618	764	1,221	3,131
Property	158	0	0	37	92	107	117	167	188	234	640	2,224
Public Spending (imputed, BEA, CSLG)	10,366	7,509	6,622	9,157	11,155	10,795	10,884	11,212	11,475	12,182	12,670	14,369
Federal (all households)	3,593	3,415	3,355	3,521	3,647	3,631	3,634	3,650	3,663	3,700	3,709	3,790
State (in state households)	6,774	4,094	3,268	5,636	7,508	7,164	7,251	7,562	7,811	8,481	8,960	10,579
Joint Filers (ASEC, %)	44	7	20	32	32	38	44	55	64	73	80	81
HH Head Filers (ASEC, %)	8	0	1	13	17	14	11	8	6	4	3	4
Single Filers (ASEC, %)	31	12	26	44	43	43	41	35	28	22	17	14
HH owners (ASEC, %)	63	51	72	56	47	52	57	65	73	79	84	85
HH size (ASEC)	2.5	1.6	1.6	2	2.4	2.5	2.6	2.8	2.9	3.1	3.2	3.3
HH head age (ASEC)	51.2	62.5	68.7	55.8	47.1	45.9	45.6	45.6	46	46.5	48.2	48.9
HH head age > 60 (ASEC, %)	32	62	81	50	26	21	18	16	16	14	16	17
HH at least one member age > 65 (ASEC, %)	27	54	74	44	21	16	13	12	11	10	11	13
N, unweighted	139,441	13,605	12,359	13,201	14,188	14,300	14,159	14,438	14,466	14,614	14,110	1,401
N, ASEC weights	252,586,791	25,258,046	25,258,014	25,258,509	25,259,012	25,256,838	25,260,217	25,258,463	25,258,130	25,260,868	25,258,380	2,526,020

Table 7: Distribution of income, taxes, and transfers in the ASEC dataset, 2015/2016. Numbers have been computed using ASEC household weights.

The column labelled "All" reports average income and tax and transfer values for the entire sample. The columns labelled "1" through "10" correspond to deciles of households ranked by household pre-government income, where each decile bin contains about the same (weighted) number of households. The column labelled "Top 1%" refers to the one percent of households with the highest incomes. All variables are in current $ or %, except "HH size" which reports number of persons, "HH head age" which is in years, "N, unweighted" and "N, ASEC weights" which report number of households. "SOI Replaced" is the share of ASEC households in each decile for whom income and tax variables are imputed using IRS-SOI data. Local income taxes are included in state income taxes for SOI replaced households and households residing in Indiana, Maryland or New York.

D Local Income Taxes

As documented by Walczak (2019), Pennsylvania was the first U.S. state to grant one of its cities (Philadelphia) authority for a local income tax (in 1932). In the 1960s, a small number of other states (mostly "Rust Belt" states) followed and allowed local governments to collect taxes from residents' incomes. Since then, local income taxes have not substantially expanded and, as of 2019, are collected in a total of 17 states. Local income taxes are levied at the level of counties, school districts, townships, cities and districts. They are collected either by state governments or directly by the local governments which impose them. Average local tax rates range up to 2.3% in Maryland (where all counties collect them). As illustrated by Figure 30 in Section A, they accounted for more than 10% of total local tax collections in six states in 2016.

We impute local income taxes paid in the ASEC dataset as follows. First, the IRS SOI data we use to replace incomes and taxes of high-income households include amounts of state and local income taxes paid (see appendix B). We use this information for SOI replaced households. Second, in addition to federal and state income taxes, the Census Bureau Tax Model imputes local income taxes in a number of states and years, namely Indiana (at least from 2007), Maryland (from 2016) and New York (at least from 2007).[50] We use these imputed amounts for non-SOI replace households.

Third, for non-SOI replaced households in all other states and years, we impute local income taxes according to this procedure; i) from the Census of State and Local Governments, we obtain data on total local income tax collections within each state and year. ii) we compute total labor income using BEA state level data on wages and salaries. iii) we construct the average local income tax rate by dividing our measure of local income tax collections by total state labor income. iv) we impute local income taxes into the ASEC dataset by multiplying household labor income by this rate.[51]

Note that, as neither the SOI data nor the ASEC dataset separately report state and local income taxes, we add the local income taxes we impute as described in the previous paragraph to the state income taxes. Hence, throughout this paper, our state income tax variable includes local income taxes.

E Consumption Taxes

This appendix lays out our approach for imputing consumption taxes. We impute these taxes as consumption times tax rates. We now lay out how we impute household consumption and the average consumption tax rates.

Consumption imputation: As a first step, we impute consumption expenditures for each good based on year, state, and household income level. To this end, we estimate consumption expenditure functions, $c_{j,t}^{CEX}(y)$ for each consumption good j in CEX. We categorize goods as follows: (1) Food at home; (2) Food away from home; (3) Alcohol;

[50] The local income taxes are included in the state income tax variable. We thank Katie Shantz for providing this information. According to its documentation, the NBER's Taxsim model does not impute local income taxes.

[51] Apart from New York City, which has the country's only progressive local income tax, our proportional model is an accurate representation of actual local income tax schedules. Also, we assume uniform local income tax rates within a state because we do not observe place of residence at the county level in ASEC for every household (let alone school district or city).

(4) Maintenance, repairs, other expenses (excluding insurance) related to the residence; (5) Other lodging; (6) Utilities, fuels and public services; (7) Housekeeping supplies; (8) Household furnishings and equipment; (9) Apparel and services; (10) Vehicle purchases (net outlay); (11) Gasoline and motor oil; (12) Other vehicle expenses (excluding insurance); (13) Public and other transportation; (14) Entertainment; (15) Personal care products and services; (16) Reading; (17) Tobacco; (18) Insurance;[52] (19) Household operations; (20) Miscellaneous; and (21) Other. Each of these categories are subject to different excise or sales taxes. All good and services that are not subject to any sales or excise taxes are lumped together in category 21 ("Other").

CEX Table 1203 reports average consumption expenditure for each good across quantiles of the income distribution. This is the basis of our consumption functions. For each income bin $n \in \{1, ..., N\}$ in the CEX tables, We calculate average income $\bar{y}_n$ and average expenditure $\bar{c}_{n,j}$ on good j. We then estimate consumption functions for each good j, $c_j^{CEX}(y)$, by linear interpolation for income in between the extreme points $y \in [\bar{y}_1, \bar{y}_N]$. For example, for $y \in (\bar{y}_1, \bar{y}_2)$ define $a \in (0, 1)$ such that $\ln y = a \ln \bar{y}_1 + (1-a) \ln \bar{y}_2$ and set

$$c_j^{CEX}(y) = a\bar{c}_{1,j} + (1-a)\,\bar{c}_{2,j}. \tag{8}$$

Outside of the extreme points for income, $y < \bar{y}_1$ and $y > \bar{y}_N$, we do log-linear extrapolation. For example, for $y < \bar{y}_1$, define $a > 1$ such that $\ln y = a \ln \bar{y}_1 + (1-a) \ln \bar{y}_2$. The imputed consumption is then given by $\ln \left[c_j^{CEX}(y)\right] = a \ln \bar{c}_{1,j} + (1-a) \ln \bar{c}_{2,j}$.

We scale the CEX-based consumption imputation by aggregate consumption of good j as recorded in the National Income and Product Accounts. The purpose is to correct for good-specific mismeasurement in CEX (Garner, Janini, Paszkiewicz, and Vendemia, 2006). By scaling to aggregate consumption we ensure that we account for all consumption tax revenue. The imputed consumption function is then,

$$c_{jt}^{IMP}(y) \equiv \frac{C_{jt}^{BEA}}{C_{jt}^{CEX}} \cdot c_{jt}^{CEX}(y), \tag{9}$$

where C_{jt}^{BEA} denotes the aggregate consumption for good j in BEA national accounts data and C_{jt}^{CEX} denotes the counterpart according CEX-based consumption functions. We calculate C_{jt}^{CEX} using the income distribution from ASEC (modified by the SOI sample), $C_{jt}^{CEX} = \sum_{i=1}^{I} \omega_i \cdot c_{jt}^{CEX}(y_i)$, where the sum is taken over all households in ASEC and ω_i represents the survey weight for household i.

We do the adjustment only for the categories we can match to PCE.[53] The following table reports the adjustment factors $C_{jt}^{BEA}/C_{jt}^{CEX}$ for 2016

[52] Insurance comprises Homeowners insurance, Vehicle insurance, Health insurance (paid by households), and Life and other personal insurance.

[53] We match all CEX categories except for (19) Household operations; (20) Miscellaneous; and (21) Other. For these categories we simply use the CEX-based imputation without any adjustment.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
2005	1.482	1.378	1.570	0.408	0.884	1.154	1.380	1.216	1.319	0.711	1.055	0.867	1.379	1.080	3.475	6.292	2.149	0.605
2006	1.503	1.400	1.591	0.404	0.919	1.190	1.380	1.207	1.302	0.643	1.155	0.871	1.367	1.100	3.538	6.088	2.242	0.593
2010	1.480	1.579	1.855	0.435	0.934	1.185	1.415	1.236	1.420	0.721	1.076	0.847	1.435	1.236	3.534	6.145	2.364	0.553
2011	1.523	1.622	1.847	0.442	0.958	1.188	1.451	1.237	1.462	0.788	1.316	0.875	1.582	1.225	3.592	5.867	2.327	0.574
2015	1.537	1.606	1.873	0.399	1.037	1.168	1.439	1.168	1.488	0.687	1.160	0.881	1.370	1.281	3.472	5.315	2.447	0.457
2016	1.549	1.634	1.914	0.387	1.008	1.164	1.443	1.184	1.482	0.670	1.032	0.913	1.324	1.315	3.472	5.409	2.574	0.452

Table 8: The table reports the adjustment factors $X_{j,t}$ calculated as ratio of aggregate consumption for various goods in BEA (Personal Consumption Expenditure) and in CEX, according to the consumption function $c^{CEX}(y)$ when evaluated at the full ASEC data given our SOI adjustment. The consumption categories are listed above.

Imputing average consumption taxes for excise-tax goods: We impute average consumption taxes for excise-tax goods based on aggregate consumption and tax revenue. We focus on excise taxes for the following six goods: tobacco, alcohol, motor fuels, public utilities, amusements, and insurance. We label these goods as "excise-tax goods."

We retrieve total state and local revenue from excise and sales taxes on each good for each state and year, T_{sjt}, from the Census of State and Local Government (for tobacco, alcohol, motor fuels, and public utilities) and the Book of States (for amusements and insurance). Federal excise tax revenue T_{Fjt} is obtained from BEA. For states where alcohol is sold via state liquor stores we add to the sales and excise tax revenue from alcohol the net revenue from state liquor stores net of expenses (data source: the Book of States).

We split the incidence of the tax revenue between households and firms. Define $\phi_j \in (0, 1]$ as the share of tax revenue on good j paid by households. For tobacco products, amusements, alcoholic beverage, and insurance, we assume that all taxes are paid by households ($\phi_j = 1$). For motor fuels we follow Minnesota Department of Revenue: Tax Research Division (2024) which estimates a share of excise taxes $\phi_{gasoline} = 2/3$ paid by households. For public utilities we assume the same split as for motor fuel, $\phi_{utilities} = 2/3$.

We calculate average sales and excise tax rates for the excise-tax good j in state s in period t based on tax revenue and the aggregates from BEA. We define the tax rates with the imputed aggregate net-of-tax consumption, denoted C_{jst}^{pretax}, as the base. The Federal tax rate can then be calculated as

$$\tau_{jFt} = \frac{\phi_j T_{jFt}}{C_{jt}^{BEA} - \phi_j \left(T_{jFt} + \sum_{s=1}^{51} T_{jst} \right)},$$

where C_{jt}^{BEA} is aggregate consumption expenditure of good j. Note that C_{jt}^{BEA} is measured including consumption taxes. The state-level tax revenue attributed to households is $\phi_j T_{jst} = \tau_{jst} * C_{jst}^{pretax}$. Our model's implied state-level aggregate consumption of good j is $C_{jst}^{IMP} = \sum_{i=1}^{I(s)} \omega_{is} \cdot c_{jt}^{IMP}(y_{is})$, where we sum over individuals in state s. Given C_{jst}^{IMP}, pretax consumption expenditure can be calculated as $C_{jst}^{pretax} = C_{jst}^{IMP} / \left(1 + \tau_{jFt} + \tau_{jst}\right)$. This implies $\phi_j T_{jst} = \tau_{jst} * C_{jst}^{IMP} / \left(1 + \tau_{jFt} + \tau_{jst}\right)$. Solving for the average state tax rate τ_{jst} then yields state-level excise tax rates of

$$\tau_{jst} = \frac{\left(1 + \tau_{jFt}\right) \phi_j T_{jst}}{C_{jst}^{IMP} - \phi_j T_{jst}}.$$

Finally, we impute sales and excise taxes for excise-tax good j in period t for a household in state s with ASEC income y_{is} using the average tax rates and the imputed consumption function (from equation (9),

$$T^{Ex}_{ijst} = \frac{\tau_{jst} + \tau_{jFt}}{1 + \tau_{jFt} + \tau_{jst}} \cdot c^{IMP}_{jt}\left(y_{is}\right). \tag{10}$$

Sales taxes for non-excise goods: **Sales taxes on goods**: The Tax Foundation reports, for every year, statutory sales tax rates τ^{SALES}_{jst}. This comprises state sales tax rates and average within-state local statutory sales tax rates. We apply these rates to most categories of goods, except for food consumed at home, drugs, and goods subject to excise taxes. Prescription and non-prescription drugs are almost universally tax-exempt, so we treat all healthcare spending as exempt from sales taxes. To the best of our knowledge, the first year for which local sales tax rates are publicly available is 2009 (Padgitt, 2009). Hence for years 2005-2006, we combine the local rates of 2009 from Padgitt (2009) with the Tax Foundation state rates for 2005 and 2006.

The total consumption taxes paid by household i in state s is then the sum over all goods,

$$T_{ist} = \sum_{j \in EXCISE} \frac{\tau_{jst} + \tau_{jFt}}{1 + \tau_{jFt} + \tau_{jst}} \cdot c^{IMP}_{jt}\left(y_{is}\right) + \sum_{j \in SALES} \frac{\tau^{SALES}_{jst}}{1 + \tau^{SALES}_{jst}} \cdot c^{IMP}_{jt}\left(y_{is}\right).$$

F Property Taxes

F.1 Imputing Property Taxes Paid by Homeowners

As described in Section 2.3, for ASEC households with income above the replacement threshold, we estimate property taxes using the IRS-SOI "real estate taxes" variable. For non-replaced ASEC owners, we impute property taxes using a hot deck approach. Specifically, we utilize ACS home owners as donors by matching them to ASEC owners on a number of relevant characteristics using a k-nearest neighbors (kNN) search algorithm.[54] The reason we match from the ACS is that, unlike the ASEC, it contains self-reported property taxes and house values of owner households.

One limitation of the ACS property tax variable is that it is top-coded at a relatively low and time invariant dollar amount ($10,000). As a result, for sample years 2015/2016, 6% of all owners are top-coded. Moreover, as shown in Figure 34, this means that the share of households at the top-code is sizable in states with high property taxes (such as New Jersey). Accordingly, the ACS probably understates the true tax burden of many households in those high tax states.

[54] We use a standard algorithm to generate a KD tree from ACS owners in a given location (county or state) based on Euclidian distances. For each ASEC owner, we then conduct the kNN search using that tree.

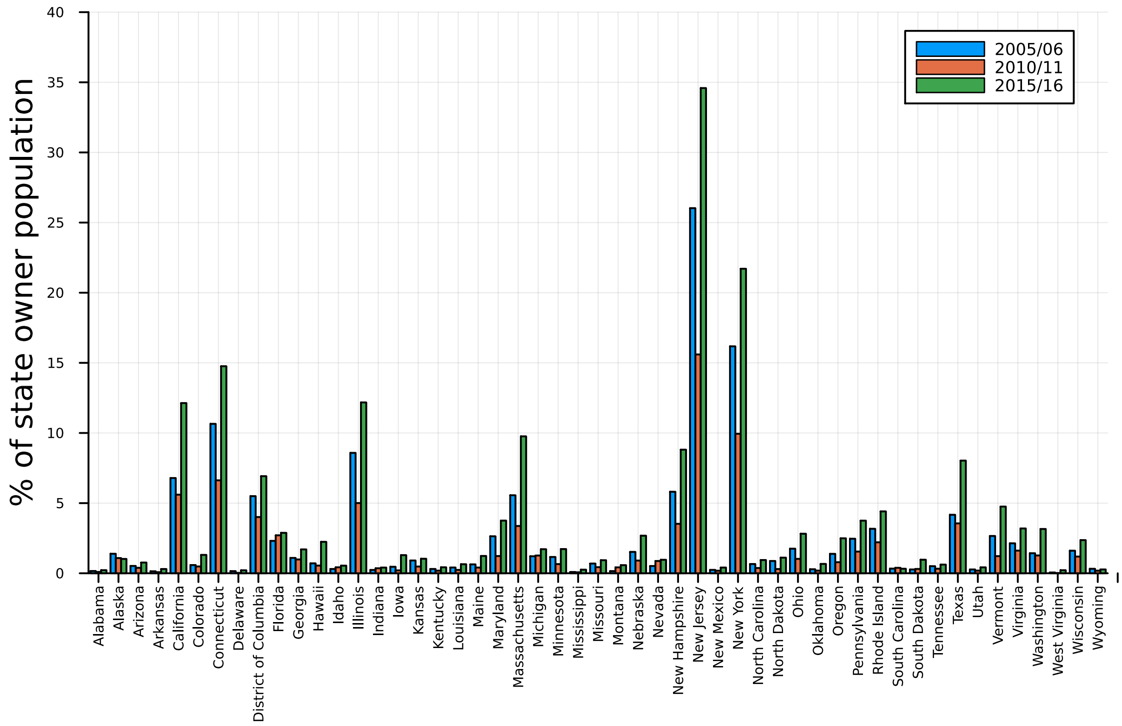

Figure 34: Share of ACS home owners with reported property taxes at the top-code ($10,000). Computed using the baseline selection conditions and ACS household weights.

Furthermore, as the left panel of Figure 35 shows, households at the property tax top code are concentrated in the highest income groups; from vingtile 15, the share of top-coded households increases from 5% to about 35% in the highest income vingtile. Because we replace ASEC households with the highest incomes by IRS-SOI ”real estate taxes”, we do not rely heavily on the top tail of the ACS income, property tax and house value distributions.[55] To further ensure that our procedure does not underestimate property taxes at the top, we use the ACS house value variable to estimate property taxes for households where the property tax value is top-coded. As the right panel of Figure 35 illustrates, top-codes for house value are less restrictive: in the 2015/16 baseline sample, only 0.84% of all household values are top-coded.[56] Moreover, almost all top-coded households are in the highest income group, where their share is just below 8%.

[55]As shown in Table 6 in Appendix C, we use IRS-SOI property tax data for about 60% of ASEC households in the highest income decile.
[56]Until 2007, the ACS house value top-code is $1m. For later years, it is state specific.

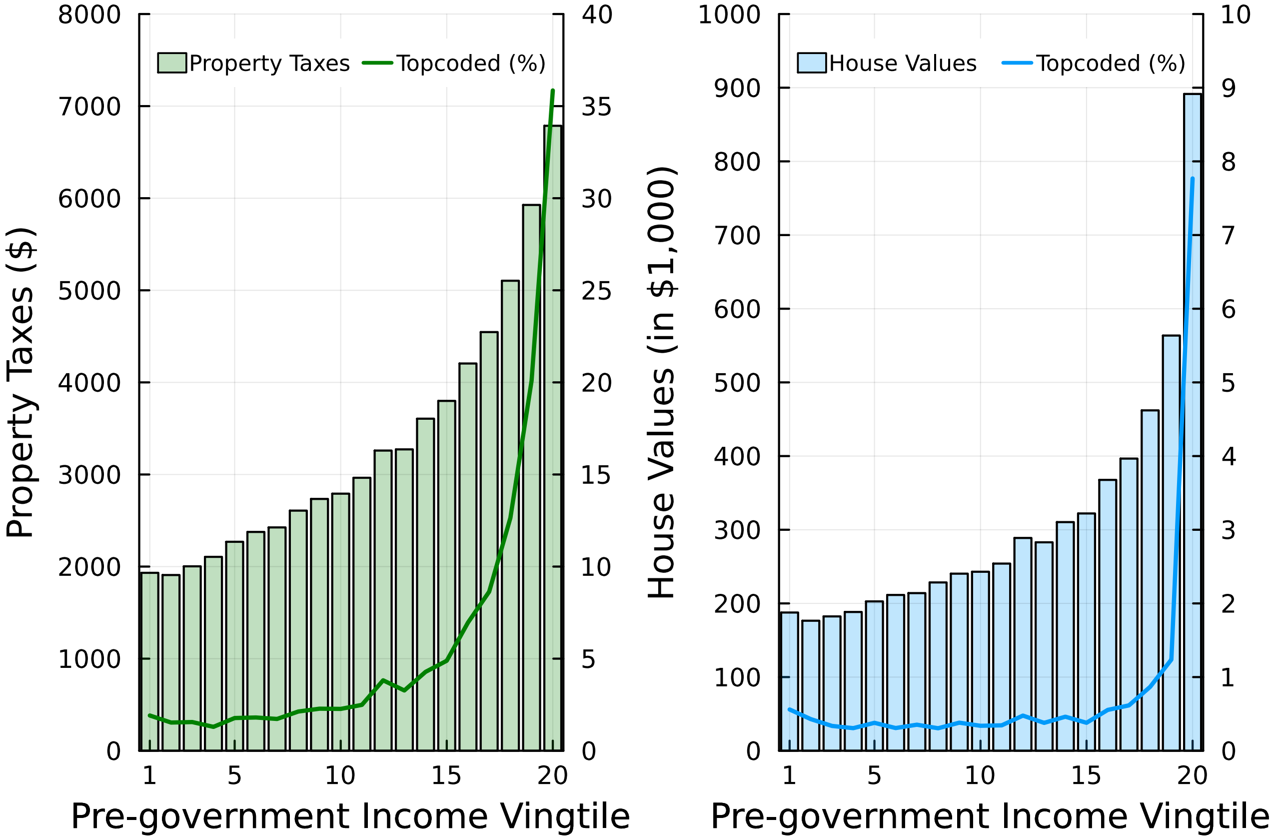

Figure 35: Left panel shows mean property taxes (left) and share at top-code (right) by income vingtile for the baseline sample. Right panel shows analogous means for house values. Source: ACS (2015/2016)

Specifically, we replace top-coded ACS property tax values as follows. For each year and state, we compute household level effective property tax rates for owners who report property taxes below the top-code by dividing their reported property taxes by their reported home values (we drop a small number of households who report higher property taxes than house values or for whom either is missing).[57] Next, for all households who are at the property tax top-code, we impute property taxes by multiplying their reported house values with the median measured property tax rate in their state, which we denote $t^p_{s,t}$.

Next, we match ASEC owners to ACS owners. First, we identify as many counties as possible in the ACS using PUMA-county equivalency files.[58] Second, we find all ASEC households with identified county of residence and for whom we can identify the same county in the ACS. For each household in this group, we find the nine nearest neighbors in the same county in the ACS. As matching variables, we use household gross income, education of the household head, and the number of housing units in the structure. Third, we match ASEC owner households that do not belong to this group (i.e. households for whom we either do not know county of residence or whose county is not identified in the ACS) at the state level, after excluding all the ACS counties which we used for county-level matching. Lastly, we compute the mean property tax from the nine nearest ACS neighbors and assign this value to the ASEC household as property taxes paid.[59]

[57]The share of households who report property taxes larger than house values is about 0.2% in the baseline sample (2015/16).
[58]We proceed as described here: https://blog.popdata.org/ipums-faqs-missing-u-s-counties/
[59]We explored using median property taxes of the ACS neighbors to limit the effect of outliers but found that this changed our results very little.

F.2 Imputing Property Taxes Paid by Renters

Renters typically do not receive a separate property tax bill but part of their rent reflects property taxes paid by their landlords on the rented unit. To capture these passed-through taxes, we impute property taxes paid by each ASEC renter using a similar approach as for owners.

We begin by estimating the value of the rented property $P_{i,c,t}$ of each ACS renter using their self-reported gross rent payments and county (state) specific price-rent ratios:

$$P_{i,c,t} = \text{Gross Rent}_{i,c,t} \times \beta_{c,t}, \tag{11}$$

where i denotes household, c is i's location of residence (county or state if county is not identified), t indicates year, and $\beta_{c,t}$ is the year and county (state) specific price-rent ratio. We obtain these ratios from Zillow and, as they are only available at the county and state level from 2010, we use time changes in the aggregate price-rent ratio published by Davis, Larson, Oliner, and Shui (2021) to estimate them for earlier sample years (2005 and 2006) and for counties with intermittent data. If we do not observe the county of the ACS renter or if there is no Zillow price-rent ratio for that county, we use the state price-rent ratio to estimate values of rented properties.

Next, we use the state- and year-specific property tax rates $t^p_{s,t}$ estimated for owners (see the previous section) to compute the property tax payable for the unit rented by renter i:

$$T_{i,c,t} = P_{i,c,t} \times t^p_{s,t} \tag{12}$$

Now, analogously to owners, we match each ASEC renter to her nine nearest neighbors in the ACS, either at the county level or, if this information is not available, at the state level. Again, we use education of the household head, household gross income, and the number of housing units in the structure as matching variables. We then impute property taxes for each ASEC renter as the mean $T_{i,c,t}$ of the nine nearest ACS neighbors. Finally, we compute the fraction of property taxes actually paid by the renter (as opposed to the landlord) by multiplying the imputed property taxes with county (state) and year specific pass-through coefficients $\gamma_{c,t}$.

$$\text{Renter Property Taxes}_{i,c,t} = \gamma_{c,t} \times T_{i,c,t} \tag{13}$$

The following section explains how we construct these pass-through coefficients.

F.3 Computing Property Tax Pass-through to Renters

We now describe the model that underlies our county-specific estimates for the fraction of property taxes paid by landlords that are passed on to tenants in the form of higher rent, as given by equation (1) and used in equation (13). In the following, technology and tax parameters that vary by county (or state) are indexed with a subscript c.

Suppose there are investors who can earn a net exogenous return ρ. One investment opportunity is buying apartments and renting them out. The return on this investment is

$$\frac{P^H_{c,t+1} + R_{c,t+1} - \delta P^H_{c,t+1} - t_c P^H_{c,t+1}}{P^H_{c,t}}$$

where $P^H_{c,t}$ is the price of an apartment, δ is depreciation, t_c is the property tax rate, and $R_{c,t}$ is apartment rent.

In a steady state, prices and rents are constant, and the return to investing in apartments must equal ρ:

$$\rho = \frac{R_c}{P^H_c} - (\delta + t_c)$$

Comparing across steady states with different values for t_c either R_c or P^H_c must adjust. We want to know how much of a dollar increase in property taxes paid passes through to R_c.

Suppose renters have aggregate income Y_c and have Cobb Douglas utility over housing and other consumption goods, with housing share in utility θ. Normalize the price of other goods to one.

Let H_c denote the stock of rental housing. We then have

$$R_c H_c = \theta Y_c.$$

On the production side, suppose rental housing is produced as a Cobb Douglas mix of land and structures, with land's share of house value denoted λ_c. Each period fraction δ of the housing stock depreciates and is replaced. Thus

$$\delta H_c = L^{\lambda_c} S_c^{1-\lambda_c}.$$

Suppose the supply of land L is completely inelastic, while the supply of structures S_c is perfectly elastic. Let P^L_c denote the endogenous price of land and P^S the exogenous fixed price of structures.

Rearranging the previous equation,

$$S_c = \left(\frac{\delta H_c}{L^{\lambda_c}}\right)^{\frac{1}{1-\lambda_c}}$$

and

$$P^S S_c = P^s \left(\frac{\delta H_c}{L^{\lambda_c}}\right)^{\frac{1}{1-\lambda_c}} = (1-\lambda_c)\delta P^H_c H_c,$$

where the second equality reflects the fact that given a Cobb Douglas technology, $(1-\lambda_c)$ is structures share of costs in housing production.

This second equality can be used to solve for the steady state house price as a function of the amount of housing produced δH:

$$P_c^H = \frac{P^s \left(\frac{\delta H_c}{L^{\lambda_c}}\right)^{\frac{1}{1-\lambda_c}}}{(1-\lambda_c)\delta H_c} = \frac{P^S \left(\frac{\delta H_c}{L}\right)^{\frac{\lambda_c}{1-\lambda_c}}}{(1-\lambda_c)}.$$

Going back to the investment return equation,

$$\rho + \delta + t_c = \frac{R_c}{P_c^H} = \frac{R_c}{\frac{P^s\left(\frac{\delta H_c}{L}\right)^{\frac{\lambda_c}{1-\lambda_c}}}{(1-\lambda_c)}} = \frac{R_c}{\frac{P^s\left(\frac{\delta\theta Y_c}{R_c L}\right)^{\frac{\lambda_c}{1-\lambda_c}}}{(1-\lambda_c)}} = \frac{R_c^{1+\frac{\lambda_c}{1-\lambda_c}}}{\frac{P^s\left(\frac{\delta\theta Y_c}{L}\right)^{\frac{\lambda_c}{1-\lambda_c}}}{(1-\lambda_c)}}.$$

The above equation defines the following mapping from t_c to R_c (every other variable in the equation is exogenous).

$$R_c^{\frac{1}{1-\lambda_c}} = (\rho + \delta + t_c)\frac{P^s \left(\frac{\delta\theta Y_c}{L}\right)^{\frac{\lambda_c}{1-\lambda s}}}{(1-\lambda_c)}$$

We can now compute the steady state response of R_c to t_c:

$$R_c = \left[(\rho + \delta + t_c)\frac{P^s \left(\frac{\delta\theta Y_c}{L}\right)^{\frac{\lambda_c}{1-\lambda_c}}}{(1-\lambda_c)}\right]^{1-\lambda_c}$$

$$\begin{aligned}
\frac{dR_c}{dt_c} &= (1-\lambda_c)\left(R_c^{\frac{1}{1-\lambda_c}}\right)^{-\lambda_c} \frac{P^s \left(\frac{\delta\theta Y_c}{L}\right)^{\frac{\lambda_c}{1-\lambda_c}}}{(1-\lambda_c)} \\
&= (1-\lambda_c)\frac{P^s \left(\frac{\delta\theta Y_c}{R_c L}\right)^{\frac{\lambda_c}{1-\lambda_c}}}{(1-\lambda_c)} = (1-\lambda_c)\frac{P^s \left(\frac{\delta H_c}{L}\right)^{\frac{\lambda_c}{1-\lambda_c}}}{(1-\lambda_c)} \\
&= (1-\lambda_c)P_c^H.
\end{aligned}$$

But what we want to know is

$$\frac{dR_c}{d(taxes_c)}$$

where

$$taxes_c = t_c P_c^H$$

$$\frac{d(taxes_c)}{dt_c} = t_c \frac{dP_c^H}{dt_c} + P_c^H$$

Now

$$\begin{aligned}
P_c^H &= \frac{R_c}{\rho+\delta+t_c} = \frac{\left[(\rho+\delta+t_c)\frac{P^s\left(\frac{\delta\theta Y_c}{L}\right)^{\frac{\lambda_c}{1-\lambda_c}}}{(1-\lambda_c)}\right]^{1-\lambda_c}}{\rho+\delta+t_c} \\
\frac{dP_c^H}{dt_c} &= -\lambda_c\left[\frac{P^s\left(\frac{\delta\theta Y_c}{L}\right)^{\frac{\lambda_c}{1-\lambda_c}}}{(1-\lambda_c)}\right]^{1-\lambda_c}(\rho+\delta+t_c)^{-\lambda_c-1} \\
&= -\lambda_c\frac{P_c^H}{(\rho+\delta+t_c)} = -\lambda_c\frac{P_c^H}{R_c}P_c^H
\end{aligned}$$

So

$$\begin{aligned}
\frac{d(taxes_c)}{dt_c} &= t_c\frac{dP_c^H}{dt_c} + P_c^H \\
&= P_c^H\left(1-\lambda_c t_c\frac{P_c^H}{R_c}\right)
\end{aligned}$$

and thus

$$\frac{dR_c}{d(taxes_c)} = \frac{\frac{dR_c}{dt_c}}{\frac{d(taxes_c)}{dt_c}} = \frac{1-\lambda_c}{1-\lambda_c t_c\left(\frac{P_c^H}{R_c}\right)}.$$

This is the expression for the pass-through $\gamma_{c,t}$ in shown in equation (1).

When $\lambda_c = 1$ (houses are all land) there is zero pass-through from taxes to rents. When $\lambda_c = 0$ (houses are all structures) there is 100 percent pass through from taxes to rents. Locally, around $t_c = 0$, the pass-through coefficient is exactly $1-\lambda_c$.

To estimate the pass-through, we need at the county (or state) level:

1. The property tax rate t_c, which we have computed (at the state level) from ACS data on house values and property taxes (see above).
2. The price to rent ratio $\frac{P_c^H}{R_c}$, which we obtain from Zillow.
3. Land's share in house value λ_c. This is available, for multiple years, and at the level of states, counties, MSAs and zip codes, from Davis, Larson, Oliner, and Shui (2021).[60]

Figure 36 plots our pass-through coefficients by county, for counties where all the inputs for equation (1) are available. We also estimate state-level pass-through rates, and use those for renters for whom we cannot identify county, or for which state-level pass-through estimates are not available. The pattern of geographic dispersion in this figure is very similar to Figure 3 of Guren, McKay, Nakamura, and Steinsson (2020) and our pass-through estimates are in line with the results of empirical investigations such as Hyman and Pasour (1973), Dusansky, Ingber, and Karatjas (1981) and Tsoodle and Turner (2008). Notably, in a recent analysis using granular information on property tax and rent changes in Alameda County (CA), Baker (2024) finds a pass-through very similar to ours (about 52%).

[60]See: https://www.fhfa.gov/PolicyProgramsResearch/Research/Pages/wp1901.aspx

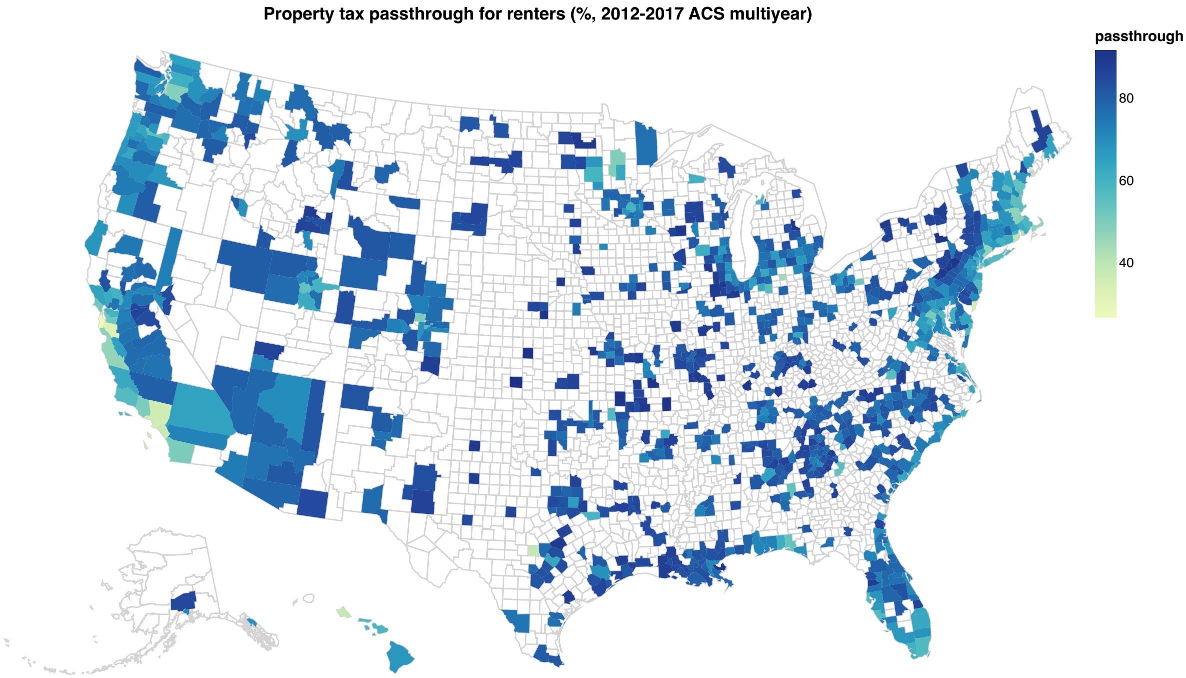

Figure 36: Property tax pass-through (in %) for renters by county; 2012-2017 ACS multi-year

F.4 Policy Determinants of Property Taxes

In this section, we describe some of the policy parameters local and state governments use to determine the amount and incidence of residential property taxes. Spatial differences in these parameters help to understand the spatial differences in property tax regressivity we document in this paper.

Equation (14) summarizes the main determinants of property taxes paid by household i on property j in year t in locality c.

$$T^P_{j,c,t,i} = \min\left\{ cb_{c,t} \times y_{c,t,i}\,, \left(\sum_{j=1}^{K} t^P_{t,c,k} \times \left(asr_{j,c,t} \times apr_{j,c,t} \times V_{j,c,t} - E_{j,c,t,i} \right) \right) - TC_{c,t,i} \right\} \tag{14}$$

Note that except for household income y and property value V, all right hand side variables are determined by policy parameters which we now explain in detail.[61]

As a first step in the property tax determination process, a property's taxable value needs to be established. The equation's innermost term shows the variables and parameters critical to this first step:

$$asr_{j,c,t} \times apr_{j,c,t} \times V_{j,c,t} - E_{j,c,t,i} \tag{15}$$

In this expression, V denotes the property value, while apr is the appraisal ratio, asr the assessment ratio and E represents (homestead) exemptions. To begin with, the fair market value of a given property is estimated in an appraisal. As documented in McCluskey, Cornia, and Walters (2012), there is a wide range of methodologies in use by different jurisdictions, with some relying on computer assisted mass appraisal methods while others apply a

[61] To the best of our knowledge, Lincoln Institute of Land Policy and George Washington Institute of Public Policy (2024) provides the most comprehensive summary on specific state-level policy choices.

judgemental approach. Hence, there is considerable variation in appraisal ratios across jurisdictions.

In the next step, the assessed value is determined, typically as a fraction of the appraised value. Twait and Langley (2018) documents that assessment ratios vary considerable across and within states states, with some state or local governments imposing assessment limits, typically by restricting the annual growth of assessed property values to a fixed percentage. Others, for example Minnesota, use a tiered assessment system which apportions house values into different assessment categories.

Lastly, the assessed amount is reduced by (homestead) exemptions to arrive at the property's taxable value. These exemptions differ across states and can be large. For example, evidence presented by Byers (2010) shows that exemptions can be up to \$50,000 in Maine but are generally zero in New Jersey. Notably, they typically depend on some characteristics of the owner i of unit j, such as their age, veteran or disability status. As a result, conditional on identical assessed values, different owners end up with different taxable values.

Next, the property's taxable value gets multiplied by the statutory property tax rate t^P:

$$t^P_{j,c,t} = \sum_{k=1}^{K} t^P_{c,t,k} \tag{16}$$

This rate is the sum of statutory rates $t^P_{c,t,k}$ set by K taxing entities (school districts, fire departments, etc.) located within a "Tax Code Area" (TCA). At this geographical level, a common set of public goods and services (schools, policing, fire protection, roads, cemeteries, etc.) is funded by property taxes.[62]

From the resulting property tax, property tax credits TC are subtracted. As Hoo (2005) documents for 2005, average credit amounts ranged from \$1,450 in Wisconsin to \$120 in California. While they are generally linked to household incomes, some counties and states make them available only to renters or do not allow them to be refundable.[63]

Finally, some counties and states have "Circuit Breaker" programs. Bowman, Kenyon, Langley, and Paquin (2009) provide a detailed description of these programs which provide targeted property tax relief, typically to low-income earners or retirees, by restricting property tax liabilities to a certain share of income:

$$T^P_{j,c,t,i} = \min\left\{cb_{c,t} \times y_{c,t,i}, \text{Property Taxes After Credits}\right\} \tag{17}$$

where $T^P_{t,s,i}$ denotes actual property taxes paid and $cb_{c,t}$ is the percentage of owner income $y_{c,t,i}$ the circuit breaker limits maximum property taxes to. According to Davis (2018), 18 states and DC had property tax circuit breaker programs in 2018 and eligibility criteria included, among others, age, disabilities, and surviving spouse status.

[62]The literature usually reports effective property tax rates computed from $\frac{\widehat{T}^P}{V} = t^P_{eff}$, not statutory rates t^P. The statutory rates are called "mill" or "millage" rates. They are often considered as determined at the county level. However, TCAs are typically smaller than counties and some counties contain hundreds of TCAs. Some state revenue departments publish the mill rates applied by jurisdictions within their state. See examples here for Georgia https://dor.georgia.gov/local-government-services/digest-compliance-section/property-tax-millage-rates and Mississippi https://www.dor.ms.gov/property.

[63]Langley (2015) compiled a detailed collection of property tax exemptions and property tax credits and uses them to study the resulting household tax savings.

F.5 Why Property Taxes are Regressive

Our measure of tax progressivity considers a tax regressive if it constitutes a larger share of current household income for low income households than for high income households. As illustrated by figure 5 in section 2.3 and tables 3, 6 and 7, this regressivity property applies for the property taxes we imputed, both in the entire ASEC dataset and for our selected sample.

Understanding if and why property taxes in the United States are regressive has been a topic of debate among economists at least since Miller (1893).[64] Answering this question from an empirical perspective is challenging because, as illustrated by equation (14), property taxes are determined by a plethora of state and local policy choices as well as by property and owner characteristics. In recent years, some of this information has become available for analysis, either by linking administrative information from different sources or in consolidated datasets, such as CoreLogic. Using this kind of data, Avenancio-León and Howard (2022) demonstrate that, after controlling for observables, the assessment ratio is generally lower for white than black home owners. As a result, black owners tend to pay higher property taxes than their white neighbors. Amornsiripanitch (2020) finds that the appraisal rate, i.e. the property value assumed for property tax determination, underestimates the negative effect of poor neighborhoods on home market values. Hence, homes in those areas tend to be overtaxed relative to homes in more affluent neighborhoods.

In the ACS, we only observe owners' self-reported property taxes T_i^P, house values V_i, incomes y_i and locations of residence (county or state). Hence, to investigate the drivers of property tax regressivity, we are restricted to a narrow set of variables. But we can decompose property taxes relative to income as the product of home values relative to income and effective property tax rates (i.e. property taxes relative to value):

$$\frac{T_i^P}{y_i} = \frac{V_i}{y_i} \times \frac{T_i^P}{V_i} \tag{18}$$

This allows us to study two different drivers of property tax regressivity using the ACS data:

1. Relative to their incomes, do low income households own or rent more expensive houses than high income households? The data in our ACS baseline sample shown in figure 6 unequivocally answer this question in the affirmative: housing expenditures, either on more valuable houses or higher rents, are non-homothetic and only slowly increase in current income.

To illustrate this source of property tax regressivity more clearly, figure 37 plots the same data as figure 6 but in ratios (house values and rents divided by incomes) instead of points in log space. The figure shows that households with low incomes tend to have the most valuable houses relative to their incomes; their homes are worth almost 12 times annual income. In comparison, for households with the highest incomes, house values represent about two times annual incomes. A similar pattern is reported by renters; renting households with the lowest incomes pay almost

[64] Some recent contributions are Oates and Fischel (2016), Levinson (2020), McMillen and Singh (2020), Avenancio-León and Howard (2022) and Amornsiripanitch (2020). There is also an ongoing debate as to whether property taxes should be considered a consumption or a capital tax.

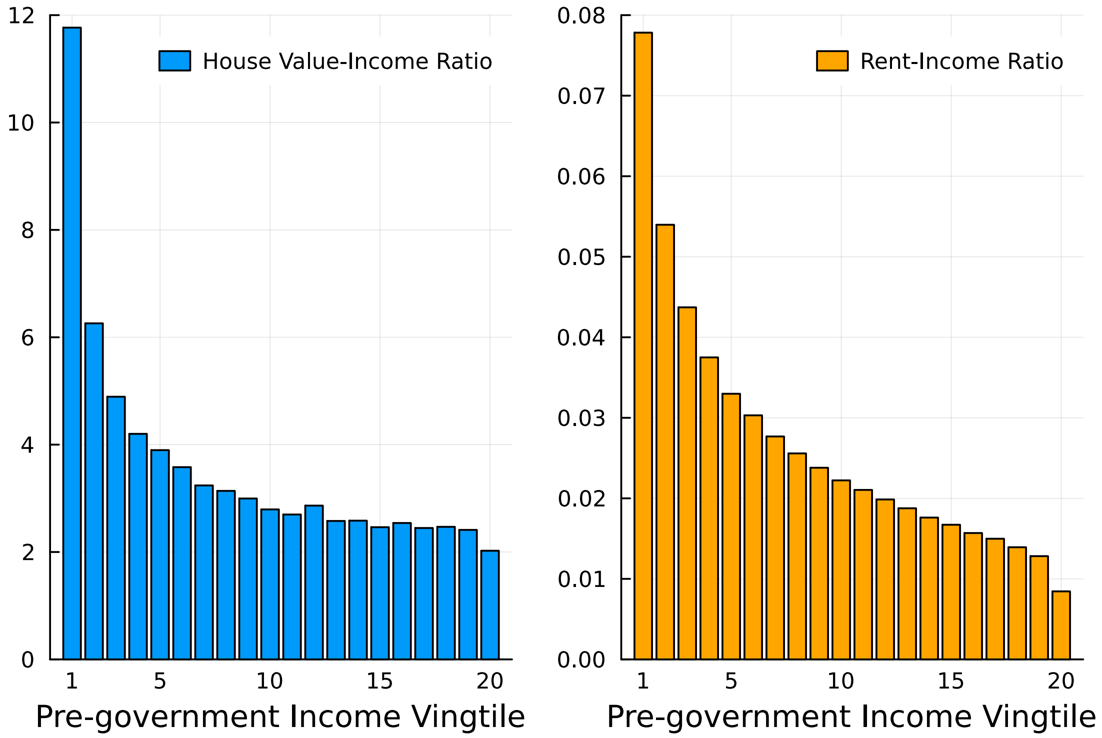

Figure 37: House value-income ratios (for owners; left) and gross rent-income ratios (for renters; right) by pre-government income. Each bar represents mean house values (rents) divided by mean pre-government income for each income vingtile, where households are ranked according to income. Source: ACS (2015/2016).

8% of their annual income in monthly rent.[65] For households with the highest incomes, this share is less than 1%.

2. Do high income households pay higher or lower (effective) property tax rates? Do circuit breakers, homestead exemptions and property tax credits translate into lower effective tax rates for low income households, introducing a source of property tax progressivity? Or are any such provisions outweighed by the fact that higher income households benefit from more favorable assessment ratios, as suggested by some of the literature cited above?

Figure 38 plots the distributions of effective property tax rates of different income groups, computed by dividing self-reported property taxes paid by self-reported house values. As the figure shows, the median property tax rate is slightly above 1.0% for all income groups (and markedly lower only for the highest income group). The mean rate, however, declines from about 1.6% for households in the lowest income group to about 1.1% for households in the highest income income group. The 90th and 95th percentile values show that this difference is driven by the tails of the rate distribution. For example, the 95th percentile value is about 3.75% for the lowest income group and then declines to about 2.4% for the highest group. The 90th percentile value shows a similar relationship to incomes, emphasizing that mean rate differences result from large effective rates reported by a few households with low incomes.[66] Households in the highest income vingtile seem to pay markedly lower effective property tax rates throughout the distribution.

[65] Note that the income measure used here refers to pre-government income, i.e. it excludes any transfers and tax credits.
[66] Recall that our baseline sample excludes retirees.

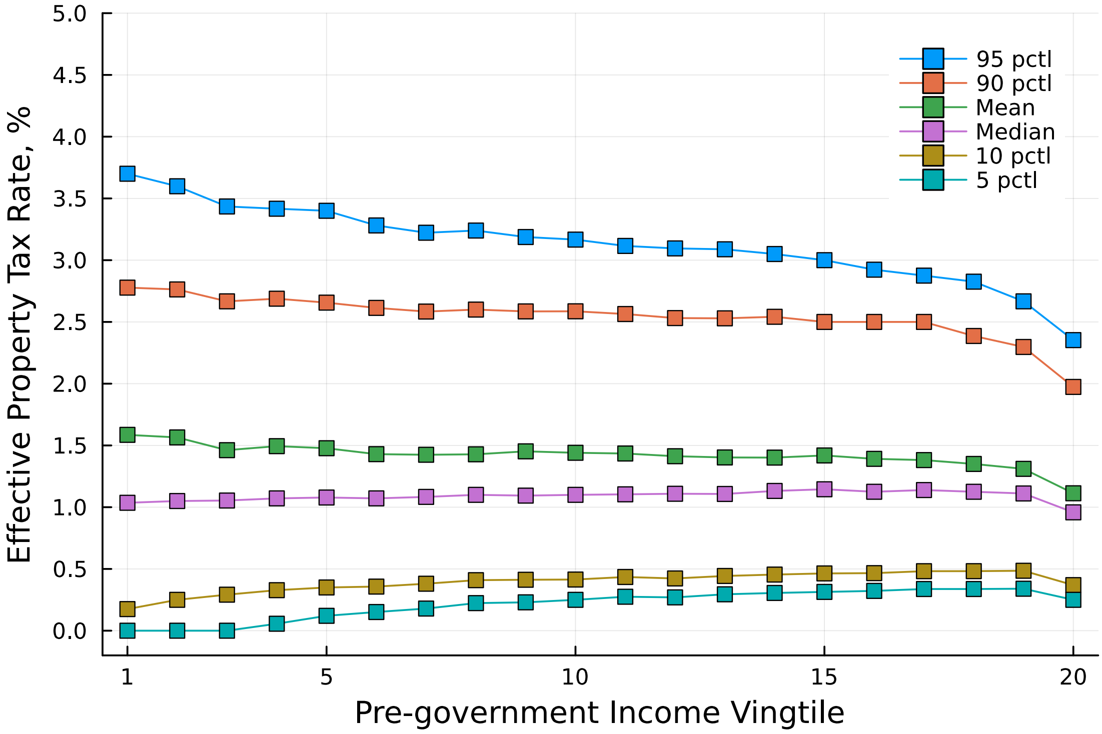

Figure 38: Mean effective property tax rates of owners in different income vingtiles (as well as mean and median), where households are ranked according to pre-government income. Source: ACS (2015/2016).

To understand why effective property taxes are lowest for households with the highest incomes, figure 39 plots the numerator and denominator (property taxes and house values) used to compute these rates separately. As previously illustrated by figure 35, both of these ACS variables have distinct top-codes and property taxes are more restricted. Importantly, in the highest income vingtile, about 35% of ACS owners are at property tax topcode while less than 8% are at the house value topcode. Figure 39 makes it clear that the restrictive property tax topcode mechanically depresses the effective property tax rate as incomes increase – the numerator can only grow slower than the denominator. For example, from the nineteenth to the twentieth income vingtile, house values increase by about 55% (from $580,000 to about $900,000) on average, while property taxes increase by only 15% (from about $6,000 to $6,900).

To sum up, the ACS data suggest that median effective property tax rates are very similar for households at different income levels, except for those with the very highest incomes. Mean rates are mildly declining as household incomes grow, as the dispersion of effective tax rates is higher for lower income groups. Note that at the highest income levels, the fact that the ACS property tax and home values are top-coded complicates estimation of effective property tax rates. Hence, as we explain in section F.1, before matching ASEC owners to ACS owners, we impute topcoded property taxes by assuming that top-coded households pay the same effective rates as non-top-coded households.

Finally, it is not clear that the self-reported data in the ACS allow to compute accurate measures of property tax rates. For example, some respondents might not know the market value of their properties and report appraised or assessed values instead. Moreover, they might not be able to report the property taxes they actually paid, especially if they received an exemption or property tax credit. To ensure that these limitations do not confound our findings

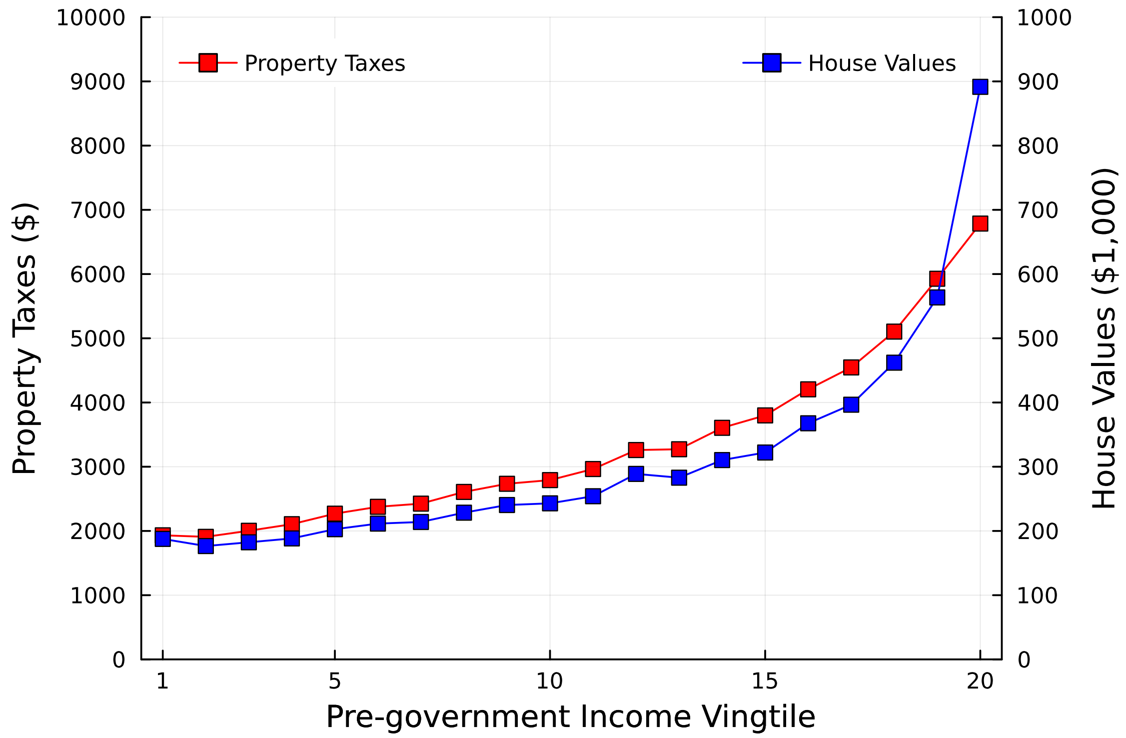

Figure 39: Mean property taxes (left) and house values (right, in $1,000) for ACS owner household in the baseline sample by income vingtile, where households are ranked according to pre-government income. Source: ACS (2015/2016).

regarding property tax regressivity, we compare the relationship between incomes and property taxes in the ACS to another survey in the next section.

F.6 Comparing Property Taxes in the ACS and AHS

To impute property taxes for most ASEC households, we match to the ACS as discussed in the previous sections. The ACS is an ideal donor dataset because it contains several identical household-level variables (which are needed for the matching procedure) and because it is representative at the state level. The ACS property tax variable has some limitations, however. First, as the focus of the ACS is not on housing, it is conceivable that the self-reported property taxes are a noisy and potentially biased measure. Second, because they are top-coded at a low level, they tend to understate property taxes paid by high income households which could make the property tax appear more regressive, despite our imputation procedure explained in section F.1.

To address these concerns, we compare the ACS property tax variable to estimates from the American Housing Survey (AHS). The AHS is the "most comprehensive national housing survey in the United States" and asks detailed questions on property characteristics, mortgages, insurance, housing costs and property taxes.[67] Importantly, the AHS property tax variable has a high top-code; its monthly value is $8,300 while the ACS annual value is $10,000. As a result, only 0.02% of the households selected using the baseline conditions are top-coded in 2015 (as opposed to 6% in the ACS baseline sample of 2015/2016).

[67] https://www.census.gov/programs-surveys/ahs.html

However, unlike the ACS, the AHS public use file provides no information on county or state of residence.[68] Hence, we have to focus on the national level for a comparison. We proceed by using the AHS 2015 variables to implement our baseline sample selection conditions and compare the mean property taxes reported by income vingtile between the ACS and AHS. The result is shown in figure 40. The ACS and AHS property tax values are almost identical for income groups up to income vingtile 15. For higher vingtiles, the AHS property taxes are either lower or about the same as the ACS property taxes. They are, however, slightly larger for the highest income group, possibly reflecting the lower ACS top-codes. In sum, figure 40 gives us confidence that our ACS-based property tax estimates accurately capture the extent of regressivity embedded in how property is taxed.

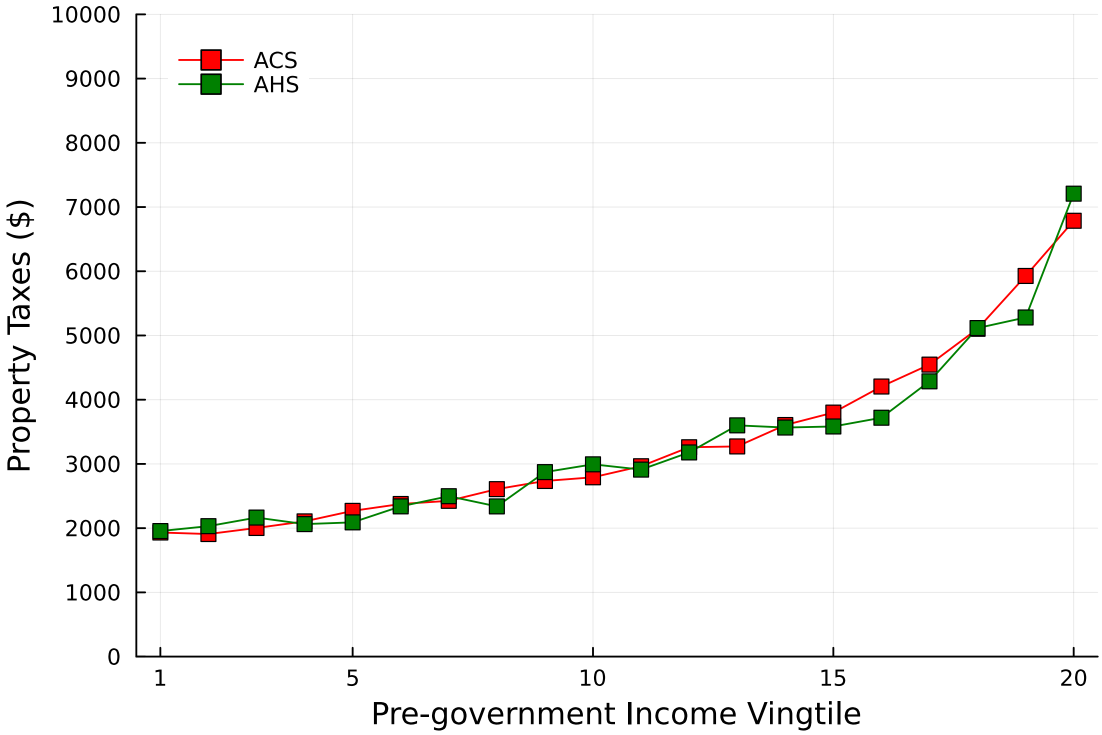

Figure 40: ACS and AHS mean property taxes by income vingtile using the baseline sample selection conditions. ACS (2015/2016), AHS (2015)

G States Tax Revenues: Dataset versus Administrative Benchmarks

The ASEC dataset does not contain any self-reported measures for taxes paid. Hence, all tax variables we are using to estimate federal and state progressivity have to be imputed. In this section, we verify that the imputed state taxes are consistent with external benchmarks. We do so by comparing per capita state tax collections in our dataset to collection numbers from the Census of State and Local Governments (CSLG). Specifically, we obtain information on total state collections for income, property and consumption taxes from the CSLG and compute per capita (i.e. per state resident) tax collections using population data from the Census Bureau Population Intercensal Estimates tables.[69]

[68] Prior to 2015, the only available geographic indicator in the AHS Public Use File is the Metropolitan Statistical Area (MSA). However, for the overall majority of records, this variable is suppressed or non-reported. Further, MSA locations imply that the AHS mostly captures property taxes of households residing in urban areas. From 2015, AHS only provides core based statistical area (CBSA) and Census Division identifiers.

[69] Available here: https://www.census.gov/programs-surveys/popest.html.

Income Taxes Figure 41 shows imputed per capita state and local income tax collections in our weighted ASEC dataset on the horizontal axis and the corresponding measure constructed from CSLG data on the vertical axis. The imputed income taxes come from two sources: For households not replaced by SOI data as described in Appendix B, they have been imputed by the Census Bureau Tax Model. For states and years for which this model does not include local taxes, we impute them as described in Appendix D. For replaced households, both state and local income taxes are imputed using SOI data. Most states in this figure are very close to the 45′ line, indicating that that Census Tax Model is very accurate, on average.

Our SOI replacement strategy explains why the ASEC dataset records small positive income tax collections in states which do not tax income, as illustrated by the data points on the horizontal axis close to the origin. The reason is that some high income households residing in such states earn income in states where income is taxable. As we cannot ascertain to which state governments these taxes are paid, we treat them as income taxes paid to the household's state of residence. This also explains why per capita income taxes collected in Washington DC are larger than in the CSLG: DC has especially many high income households with income tax obligations in other states.

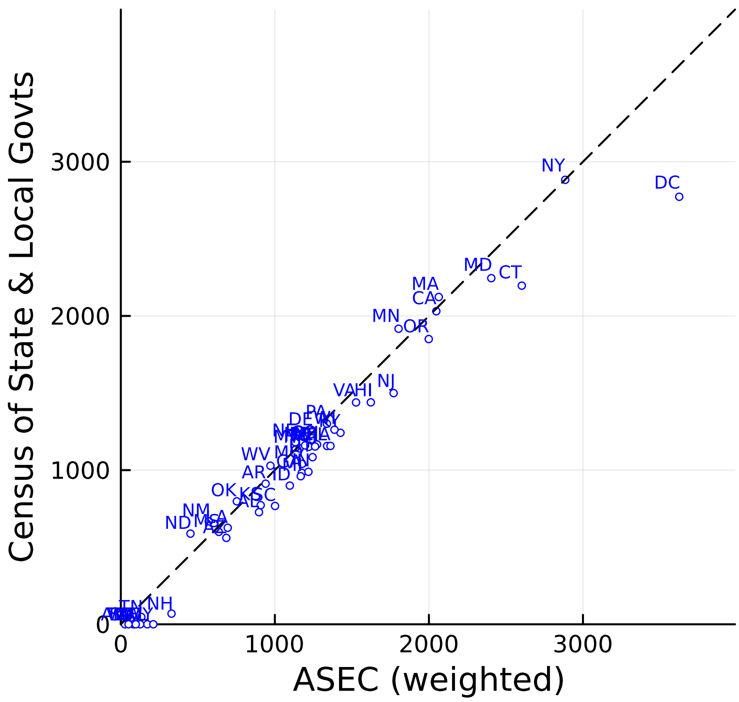

Figure 41: Per capita state and local income tax collections in current $, in the ASEC dataset (horizontal axis) and the Census of State and Local Governments (vertical axis) for 2015 and 2016.

Property Taxes Figure 42 shows per capita household (non-commercial) state and local property tax collections from the CSLG and the (weighted) ASEC dataset. The CSLG reports total (household and commercial) property taxes collections and we use the numbers reported by Ernst and Young (2016) on commercial property taxes collections to construct a measure for property taxes collected from households only. As the numbers of Ernst and Young (2016) include property taxes on rental units, we use only property taxes paid by owners (on owner-occupied dwellings) from the ASEC dataset for comparison. These taxes are imputed as described in Appendix F.1.

For the majority of states, the fit is remarkably accurate. Relative to the CSLG/EY numbers, our ASEC dataset misses some property taxes in small states (Wyoming) and in states with especially large per capita property taxes (Connecticut, New Hampshire), indicating that our estimates of property tax regressivity constitute lower bounds in those states.

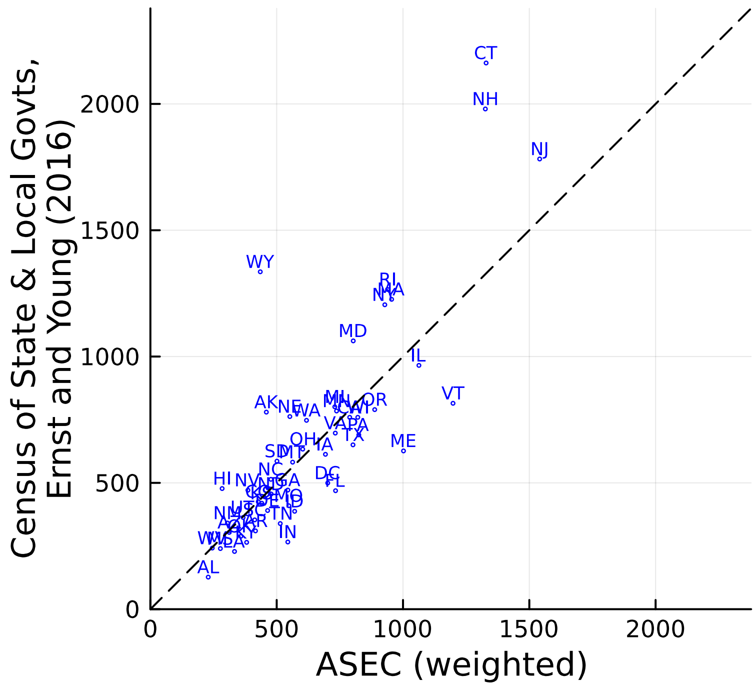

Figure 42: Per capita state and local household property tax collections in current $, in the ASEC dataset (horizontal axis) and the Census of State and Local Governments (vertical axis) for 2015 and 2016. Commercial property tax collections have been excluded using the data provided by Ernst and Young (2016).

Consumption Taxes We impute sales and excise taxes for all ASEC households as described in Appendix E. Figure 43 compares the per capita consumption taxes (the sum of sales and excise taxes) in the ASEC dataset to the sum of the corresponding CSLG revenue categories. As the CSLG also includes taxes collected from businesses, we again use data provided by Ernst and Young (2016) to construct a measure for taxes paid by households only.

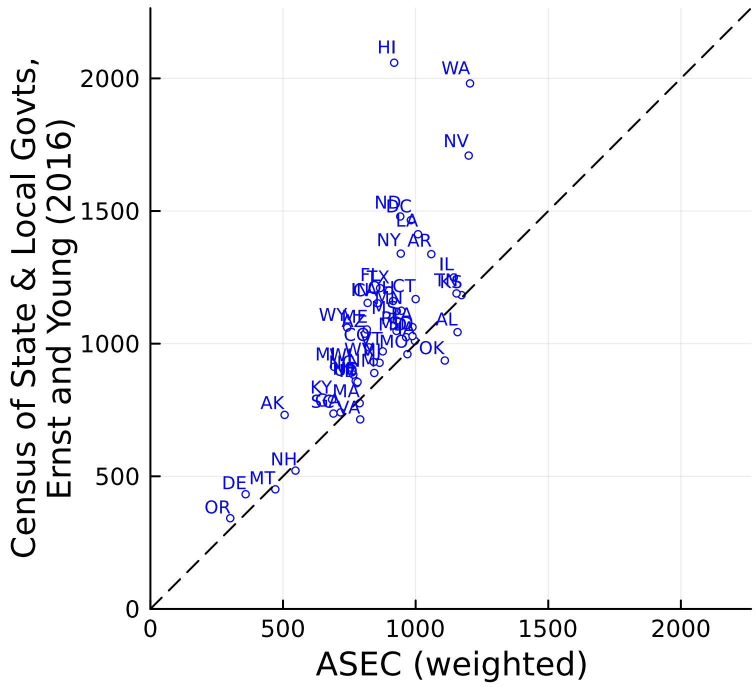

Figure 43: State per capita consumption tax collections, in $ for 2015 and 2016.

Overall, the administrative and imputed tax aggregates are strongly positively correlated but the imputation model tends to assign lower taxes paid than the administrative benchmark, resulting in lower average tax rates. This is particularly true for some states, for example Hawaii, Washington and Nevada. Recall that our model assumes all spending is done by state residents. But for Hawaii and Nevada, spending by tourists is an important additional source of revenue. Similarly, residents of states bordered by states with no sales tax (for instance New Hampshire and Oregon) might be paying less consumption taxes than our model imputes. The discrepancies could also be due to Ernst and Young (2016) underestimating sales and excise taxes paid by businesses. For example, Ernst and Young (2016) imputes that businesses in Hawaii pay about 40% of general sales taxes, which is the same level as they impute for the nation as a whole. However, different from the rest of the U.S., businesses in Hawaii pay sales taxes on all intermediate inputs, so their share of aggregate sales taxes are likely to be larger than in the rest of the nation.

H Transfers

We now give additional details on six transfer programs: Supplemental Nutrition Assistance Program (SNAP, "Food Stamps"), Temporary Assistance for Needy Families (TANF), Housing Assistance, Alaska Permanent Fund Dividends (APFD), Medicaid, and the annuitized value of accrued Social Security benefits.

H.1 Supplemental Nutrition Assistance Program (SNAP)

SNAP is a federal transfer program administered by the Food and Nutrition Service of the Department of Agriculture (USDA). According to the USDA, it aims to provide "food benefits to low-income families to supplement their grocery budget so they can afford the nutritious food essential to health and well-being". We consider SNAP a federal transfer program as states have minimal options regarding eligibility and generosity and provide only a negligible fraction of the funding. This is concisely summarized by Hoynes and Schanzenbach (2015) who write that "SNAP is a federal program with all funding (except 50 percent of administrative costs) provided by the federal government, eligibility and benefit rules determined federally, and comparably few rules set by the states. [..] The eligibility rules and benefit levels vary little within the U.S., and are largely set at the federal level."[70]

As a measure for SNAP receipts, we use the variable imputed into the ASEC dataset by the CBO. As explained in Habib (2018), it uses administrative data on SNAP spending to correct for under-reporting, but information on self-reported SNAP recipiency which captures take-up differences across states. These differences have been documented, for example, by Figure 4 of Bleich, Moran, Vercammen, Frelier, Dunn, Zhong, and Fleischhacker (2020), and can be explained by two factors. First, SNAP benefits are not indexed to local prices but are uniform nationwide which leads to regional differences in SNAP take up rates.[71] Second, even though state governments have relatively few SNAP "state options", they have some flexibility to expand eligibility – e.g. by allowing higher income and asset limits and including people who already qualify for TANF or Medicaid ("categorical eligibility") – and states can also reduce application burdens, e.g. by automatically testing for SNAP eligibility of unemployment insurance applicants.

H.2 Temporary Assistance for Needy Families (TANF)

The welfare reform of 1996 introduced the Temporary Assistance for Needy Families (TANF) program as a successor to Aid to Families with Dependent Children (AFDC).[72] Federal funding contributions to state TANF spending occur through block grants and grant sizes were determined by a state's historical spending on welfare programs related to AFDC. Hence, the relative size of the federal TANF block grants differ substantially because per capita AFDC spending varied greatly among states.[73] For example, as of 2014, the national average of the federal TANF block grant relative to the number of children living in poverty is \$1,190 but ranges ranges from \$293 in Texas to \$3,154 in Washington, DC, as documented by Hahn, Aron, Lou, Pratt, and Okoli (2017).

Under the TANF program, states face almost no federal parameters on program eligibility or spending objectives. To keep receiving the federal block grant, they must only continue to spend a fraction of their historical welfare spending.[74] As a result, the TANF program has two distinct features. First, even conditional on receiving the same per-capita amount of federal TANF funding, the actual use of funds varies drastically across states because each state sets its own rules on eligibility, generosity and duration. Schott, Pavetti, and Floyd (2015) and Hahn, Aron, Lou, Pratt, and Okoli (2017) document this feature of TANF in detail. Second, there is enormous cross-state variation in terms of actual TANF spending. Two examples from Hahn, Aron, Lou, Pratt, and Okoli (2017) are illustrative. First, "in 1998, for every 100 families with children in poverty, California provided cash assistance to more than three

[70] 50 percent administrative cost account for about 5% of total SNAP spending according to Center on Budget and Policy Priorities (2022).
[71] See Hoynes and Ziliak (2018) for details on spatial heterogeneity in the purchasing power of SNAP benefits.
[72] Ziliak (2015) provides a comprehensive description of the TANF program.
[73] See Moehling (2007) for a lucid summary on the evolution of state welfare systems.
[74] This Maintenance of effort (MOE) requirement is about 75% of AFDC spending.

times as many families as Texas did. By 2013, the corresponding factor had grown to 13 times as many families. Second, ”as of 2014, the maximum monthly benefit for a family of three with no other income averages $436 and ranges from $170 in Mississippi to $923 in Alaska.”

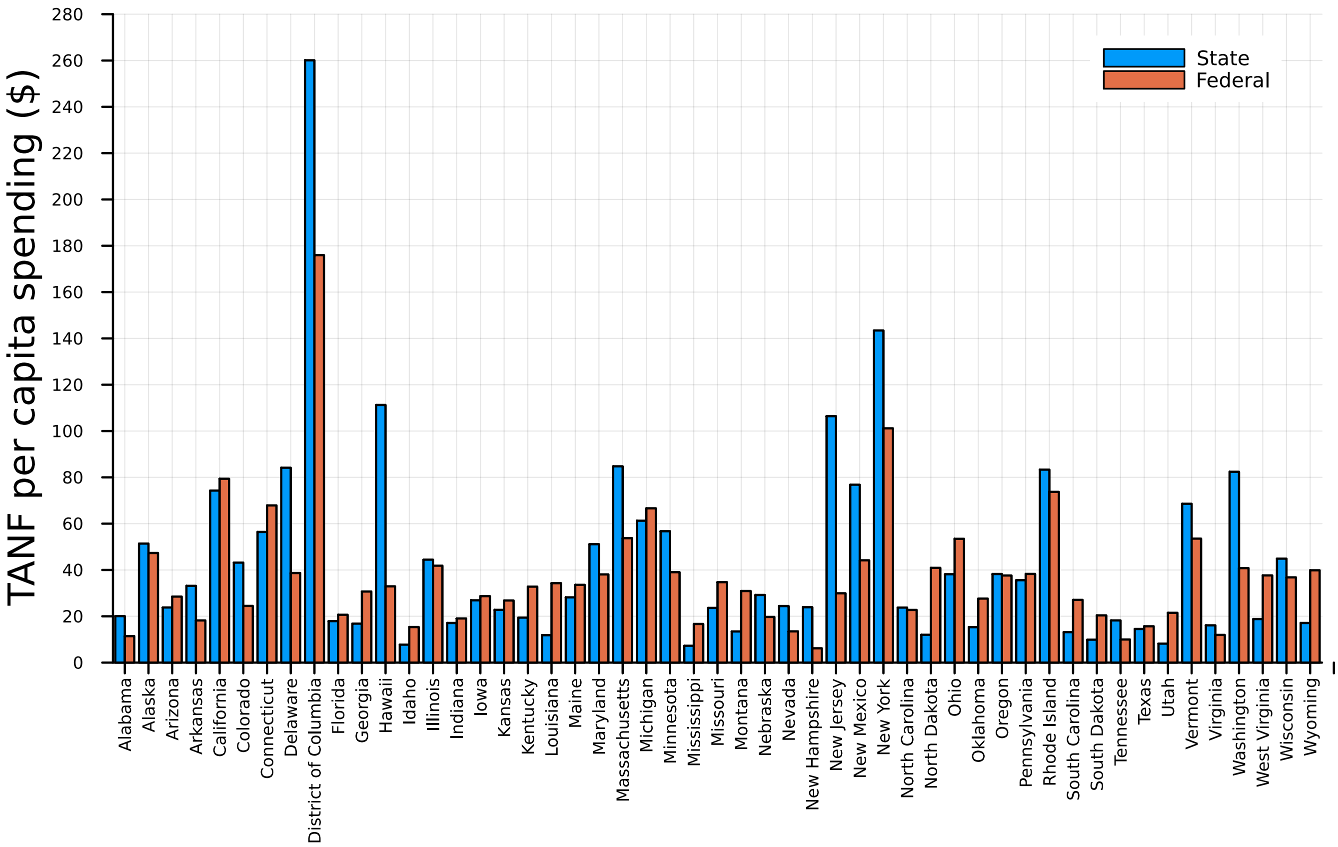

Figure 44: Federal and State per capita TANF spending in 2016. Computed from TANF Financial Data provided by the Office of Family Assistance (OFA).

For 2016, Figure 44 uses administrative data to illustrate the cross-state differences in total federal and state per capita TANF spending. State spending ranged from $8 in Idaho to $260 in Washington, DC while Federal spending was $6 in New Hampshire and $175 in Washington DC. To capture these cross-state differences in TANF transfers, we measure benefits at the household level using the ASEC variable INCWELFR.[75] To split the reported numbers into federal and state components, we use program data from the Office of Family Assistance (OFA).[76]

H.3 Housing Assistance

We include housing assistance provided by the federal government as a household transfer but abstract from state housing assistance programs because they are negligible in comparison to federal expenditures. For illustration, Pelletiere, Canizio, Hargrave, and Crowley (2008) estimate that in 2008, across all states, state spending on housing

[75] As the ASEC questionnaire asked respondents to report ”cash assistance” for this variable, it might include additional forms of state and local cash transfers.

[76] https://www.acf.hhs.gov/ofa/programs/tanf/data-reports. We obtain data on federal and state total TANF spending for 2010. As federal TANF block grants are fixed, we use the 2010 data to approximate the federal versus state split for the other years included in our sample. The resulting state (federal) shares range from 17% (83%) in West Virginia to 71% (29%) in Washington with a national mean of 42% (58%).

assistance amounted to $1.7bn compared to the nearly $30bn spent on the three major federal housing assistance programs (public housing, Section 8 project based housing, and Section 8 vouchers).[77] To measure the household transfers provided by federal housing assistance support, we use the respective variable imputed into the ASEC dataset by the CBO.[78]

H.4 Alaska Permanent Fund Dividends (APFD)

Using data from the Alaska Permanent Fund Corporation, Berman and Reamey (2016) report that more than 90% of Alaska residents receive Alaska Permanent Fund Dividends (APFD) every year. Those dividends vary by year but are typically around $1,200 per capita.[79] However, they are under-reported in ASEC for two reasons. First, the ASEC questionnaire does not have a specific APFD question. Berman and Reamey (2016) point out that many Alaskan respondents might report APFDs in the question "Other Income".[80] Yet, they also observe that only about one-third of respondents in Alaska reported positive "Other Income" and conclude that respondents might also report APFD dividends as dividend, interest or rental income. Second, APFDs are disbursed to Alaska residents independently of their age, but ASEC does not collect incomes of respondents younger than 15 and it is unclear whether parents responding to the survey report dividends received on behalf of their children.

To address this APFD under-reporting in our dataset, we create a new APFD variable and treat it as a state transfer. We proceed as follows:

1. To each Alaskan household, we impute a year specific APFD entitlement using the number of household members and the per capita amounts reported by Berman and Reamey (2016).
2. For each of the four non-labor income variables (other, dividend, interest, rental) we check if reported amounts are at least as large as 75% of the APFD entitlement.
   - If true for at least one of these variables: we assume the household has reported the APFD, subtract it from the respective income variable and assign it into the APFD variable.
   - If false: we assume the household has not reported the APFD and assign the entitled amount into the APFD variable.

H.5 Medicaid and CHIP

Medicaid and the Children's Health Insurance Program (CHIP) provide medical assistance payments to certain individuals. According to Medicaid and the CHIP Payment and Access Commisson (2018b), Medicaid and CHIP expenditures in 2016 totalled $583bn (equivalent to 3.1% of GDP) and represented about 17.4% of total national health expenditures.[81] As of December 2016, the programs covered about 75 million beneficiaries (one in five Amer-

[77] Congressional Budget Office (2015) provides a comprehensive summary of these different programs and their expenditure breakdowns as well as an overview on eligibility and generosity.
[78] See https://github.com/US-CBO/means_tested_transfer_imputations
[79] For example, for the years 2015 and 2016, they amounted to per capita payments of $2,072 and $1,022 respectively.
[80] Indeed, in our sample, the mean of this variable in Alaska is ten to twelve times larger than in other states.
[81] The other sizable payers were Medicare (20.1%) and private insurances (34%).

icans), making it the by far largest means-tested transfer program in the US, both with respect to expenditures and recipients. Moreover, expenditures and enrollment have expanded by a factor of 20 since the 1980s and the program keeps growing. Indeed, during our sample time period alone, i.e. from 2005 to 2016, Medicaid expenditures grew by more than 85% and enrollment by more than 55%.[82]

Cross-state differences in enrollment and spending Federal guidelines require states to provide Medicaid and CHIP to certain individuals and to cover expenditures on certain types of medical services. In general, mandatory recipients are individuals in four groups (children, adults – either pregnant women or parents – individuals with disabilities and elderly individuals) if their incomes are below a certain percentage of the Federal Poverty Limit, their financial resources fall below certain limits, or they are eligible for other social assistance programs. For example, all states must cover pregnant women with family incomes below 133 percent of the federal poverty level (FPL) or disabled individuals who receive assistance through SSI. Mandatory medical services include, for instance, hospital and nursing home care as well as x-rays and immunizations.

However, as ”Medicaid is a cooperative program between the Federal and State governments” (Department of Health and Human Services, 2016), it features numerous state options, allowing states to include optional recipients and to provide optional services. As optional pathways to eligibility, states my choose higher FPL percentages for income tests, increase resource limits, or establish ”medically needy” individuals by considering their medical expenses.[83] As a result, as of 2013, the share of Medicaid recipients that were mandatory under federal guidelines (as opposed to state optional) ranged from 35% in Vermont to 96% in Nevada. Cross-state differences in eligibility and enrollment increased even further after the Affordable Care Act (ACA, ”Obamacare”) took effect in 2014 as it allowed states to expand eligibility to non-elderly adults with incomes up to 133% of the FPL. As documented by the Congressional Research Service (2021), 25 states expanded Medicaid coverage in that same year and, by 2016, seven more states had followed. As a result, through these ”Newly Eligible Adults”, the number of adults covered in expansion states increased sharply in between our sample years, as shown in Figure 45.

[82] Buchmueller, Ham, and Shore-Sheppard (2015) provide a comprehensive overview on this complex transfer program.

[83] Schneider, Elias, and Garfield (2002) and the Medicaid and the CHIP Payment and Access Commisson (2017) provide an exhaustive description of state pathways into Medicaid.

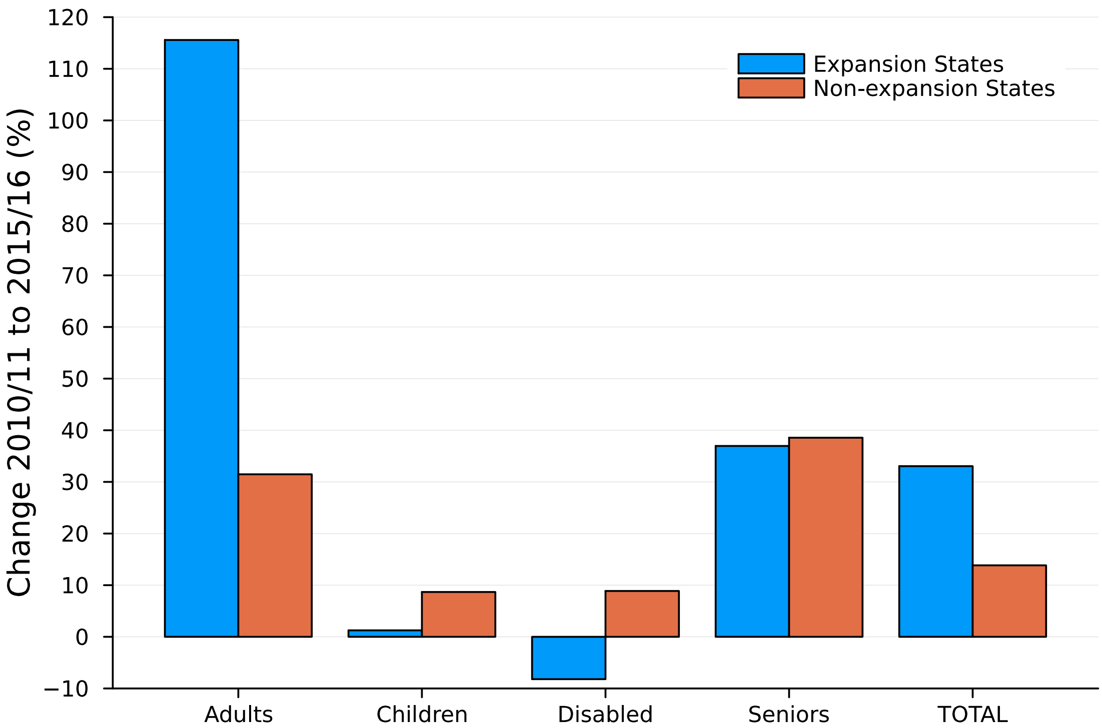

Figure 45: Change in Medicaid Enrollment by State between 2010/11 and 2015/16. Changes are computed using data provided by the Centers for Medicare & Medicaid Services (CMS), the Kaiser Family Foundation, and the Medicaid and CHIP Payment and Access Commission (MACPAC).

As for eligibility, many states go above the mandatory guidelines and cover optional services such as prescription drugs as well as dental and vision care.[84] Others restrict spending on services through various rules, for example by limiting the number of hospital days or the number of visits to physicians per year. Moreover, while Medicaid beneficiaries are entitled to have payment made on their behalf for covered services that are "necessary", states have flexibility in defining which services meet the "medical necessity" definition. As a result, there is large cross-state variation in Medicaid covered benefits that can be summarized as "each state's Medicaid benefits package is unique" (Schneider and Garfield, 2002).

To summarize the effect of Medicaid and CHIP's mandatory and optional parameters, Figure 46 shows average spending per recipient (left) for 2016 and the share of each state's population who was enrolled at some point during that year (right). Spending per recipient ranged from about $3,400 in Alabama, Florida, Georgia, Nevada and South Carolina to about $8,500 in Washington DC, North Dakota and Vermont. Enrollment was less than 15% of the state populations of Idaho, Kansas, Nebraska, North Dakota, South Dakota, Utah, Virginia and Wyoming and above 30% in Arkansas, DC, Kentucky, Louisiana, New Mexcio, New York, Vermont and West Virginia.

[84] Schneider and Garfield (2002) provide a detailed list of mandatory and optional benefits and Snyder, Rudowitz, Garfield, and Gordon (2012) document and discuss state differences in Medicaid spending.

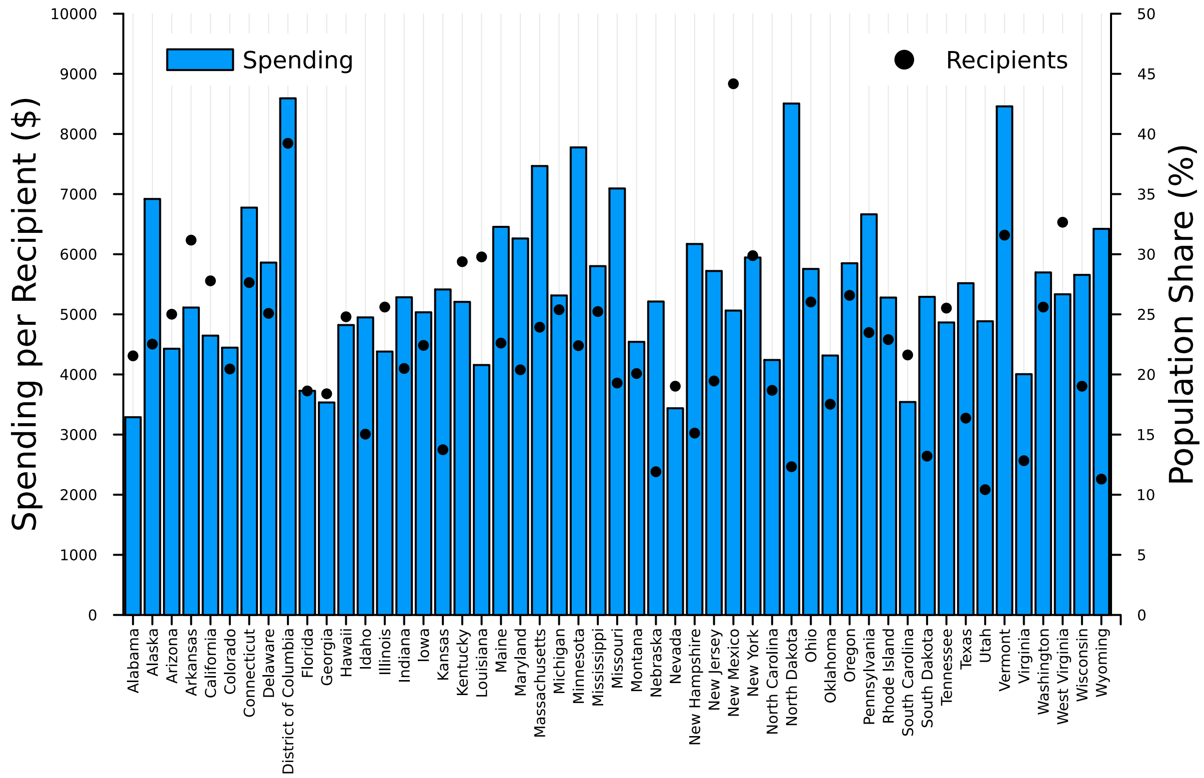

Figure 46: Medicaid spending per recipient (left axis) and Medicaid recipients as share of state population (right axis), 2016. Recipients include part-year recipients. Source: Centers for Medicare & Medicaid Services (CMS), Kaiser Family Foundation, Medicaid and CHIP Payment and Access Commission (MACPAC).

Measuring enrollment and transfer benefits in ASEC The ASEC survey asks respondents to report Medicaid or CHIP coverage. However, as documented by Habib (2018), coverage tends to be under-reported by almost 50% relative to administrative information in recent years, as many recipients might not be aware they are covered or might confuse Medicaid and CHIP with other welfare programs (especially Medicare). Like other surveys, ASEC does not ask respondents to report Medicaid or CHIP amounts received, because recipients generally have no information on expenditures made on their behalf because they never receive bills nor are required to pay out of pocket.

The Congressional Budget Office (CBO) has developed an algorithm which corrects for the ASEC Medicaid and CHIP under-reporting and provides person-level estimates for the transfer amounts provided by these programs. As documented in Habib (2018), their algorithm uses self-reported coverage data to estimate a model of enrollment probabilities, and assigns recipiency until the number of ASEC recipients meets administrative targets developed from national enrollment data for the different groups (children, seniors, disabled and adults). For each imputed recipient, the algorithm then assigns expenditures derived from national administrative spending information, allowing for some heterogeneity within enrollment groups to capture differences in within-year coverage periods.[85]

However, there are two limitations of the CBO algorithm for the study of spatial heterogeneity in Medicaid and CHIP enrollment and spending. First, the algorithm targets national totals but does not account for the differences in enrollment by state documented above. Second, it does not use state specific spending numbers but assumes that spending on the different groups is identical in all states. To capture those dimensions of regional heterogeneity, we

[85]We thank Bilal Habib for answering questions on the algorithm.

adjust the CBO's algorithm by (i) targeting state-level enrollment numbers, and (ii) using state average spending for each enrollment group.[86]

Another adjustment we make is that we only consider 40% of the imputed administrative spending as a person-level transfer, and refer to this as the Medicaid and CHIP "cash value". This 40% share is based on Finkelstein, Hendren, and Luttmer (2019), who argue that the remaining 60% of Medicaid spending effectively benefits agents other than Medicaid enrollees, including hospitals which, absent Medicaid, would face large costs of providing uncompensated care. The actual willingness to pay for Medicaid by enrollees may be smaller or larger than this 40% of spending value.

Accounting for federal and state financing Medicaid and CHIP are jointly financed by both federal and state governments. In 2016, the federal government's share in financing Medicaid was 63% of total spending and 82% for CHIP.[87] Federal contributions come from a matching grant, and the share of Medicaid costs paid by the federal government is determined by the Federal Medicaid Assistance Percentage (FMAP). This percentage is given by the following function of a state's average income relative to national average income:

$$FMAP_{s,t} = \min\left\{ \max\left\{0.83, 1 - \frac{(y_{s,t})^2}{(y_{US,t})^2} \times 0.45\right\}, 0.5\right\}, \tag{19}$$

where y_{st} denotes average per capita income in state s, and $y_{US,t}$ denotes average per capita income in the United States. Hence, the federal government pays a larger share of Medicaid costs the lower is state income (but it never pays more than 83% or less than 50%). For our sample years, FMAPs are shown for every state in Figure 47.[88]

[86]We collect data on state-level Medicaid and CHIP enrollment for all groups as well as average spending amounts from the Kaiser Family Foundation, Centers for Medicare & Medicaid Services (CMS) and the Medicaid and CHIP Payment and Access Commission (MACPAC). Fleck (2024) provides more details and a comprehensive documentation and evaluation of our algorithm.

[87]See Department of Health and Human Services (2017) and Medicaid and the CHIP Payment and Access Commisson (2018a). Schneider and Rousseau (2002) provide a comprehensive description of Medicaid financing.

[88]Note, as mentioned by Buchmueller, Ham, and Shore-Sheppard (2015), Washington DC's FMAP has been set at 70% since FY 1998. Moreover, Congress may decide to temporarily increase FMAPs to address economic crises or public health emergencies, such as the COVID-19 pandemic.

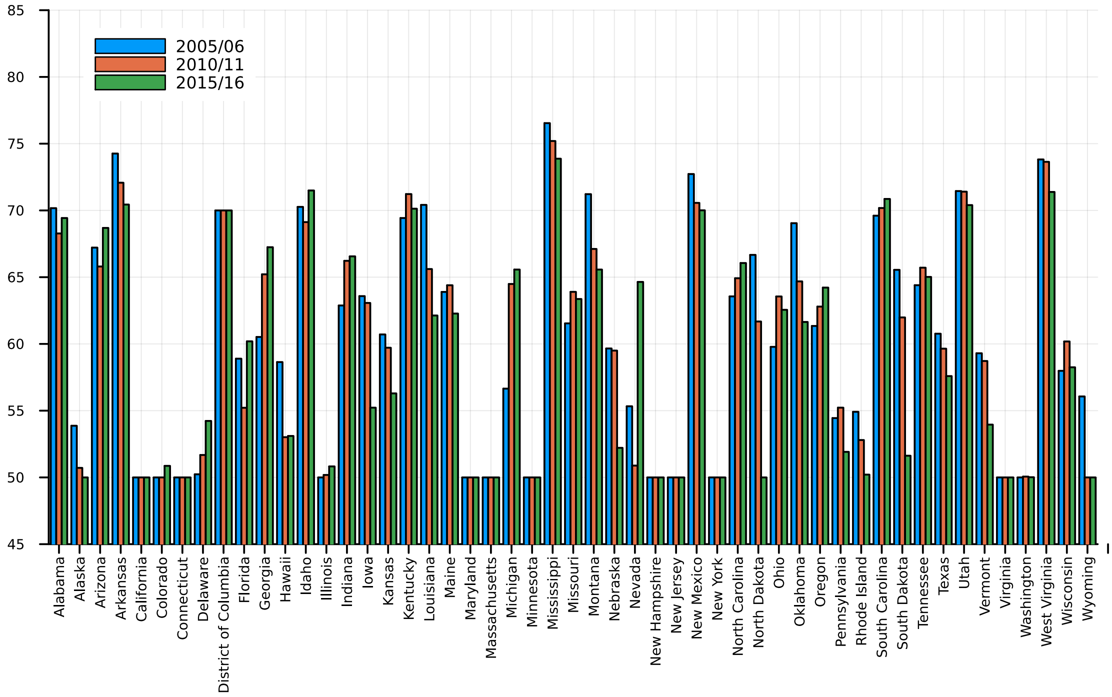

Figure 47: Federal Medicaid Assistance Percentages (FMAPs), averages of adjacent years. Source: Federal Register.

The National Association of State Budget Officers (2017) documents that states dedicated, on average, 28.7% of their total expenditure to Medicaid in 2016. However, due to different FMAPs and differences in state-level Medicaid eligibility and generosity options, spending ranged from 11.4% in Wyoming to 37.7% in Ohio. In our imputation algorithm, we apportion person-level Medicaid and CHIP transfer amounts into state versus federal shares using the Federal Medicaid Assistance Percentages (FMAPs).[89]

H.6 Medicare

Medicare is a federal program which provides health insurance for retirees as well as for younger individuals with certain health conditions. The program is sizable: it accounts for about one fifth of total national spending on healthcare and for about ten percent of the federal budget. Despite being a federal program, regional variation in spending per enrollee is substantial due to regional differences in cost and utilization.[90]

The ASEC dataset does not contain any self-reported measures for the value of Medicare benefits received. However, Medicare enrollment is accurately reported and closely matches administrative numbers.[91] Hence, to impute Medicare transfers, we use ASEC (person level) self-reported enrollment, age, year, and state of residence, as well as data on state level Medicare per enrollee spending provided by the ”Centers for Medicare & Medicaid Services”

[89] Kaiser Family Foundation (2012) and Congressional Research Service (2020) describe and compare FMAPs, enhanced FMAPs and E-FMAPs (for CHIP). As the quantitative differences are minor and as we cannot identify Medicaid spending components reimbursed according to the different percentages, we work with FMAPs.

[90] According to Super (2003), spending in one state can be about 50% of spending in another state. As noted by CMS (2020), ”States with per enrollee Medicare personal health care spending above the U.S. average were generally located in the eastern United States. The states with the lowest spending were generally in the western United States that have less densely populated areas with younger enrollee populations.”

[91] See Habib (2018), Appendix B.

(CMS).[92]

The state level data are not available for different age groups, but the CMS documents substantial spending differences at the national level: in 2016, spending on enrollees below age 18 was about five times mean spending, while spending on enrollees older than 85 was about double. To account for these age differences in our imputations, we use the national age spending pattern (as percentage deviation from mean spending) to adjust state spending for three distinct age groups. The resulting state per enrollee spending numbers are shown in Figure 48.

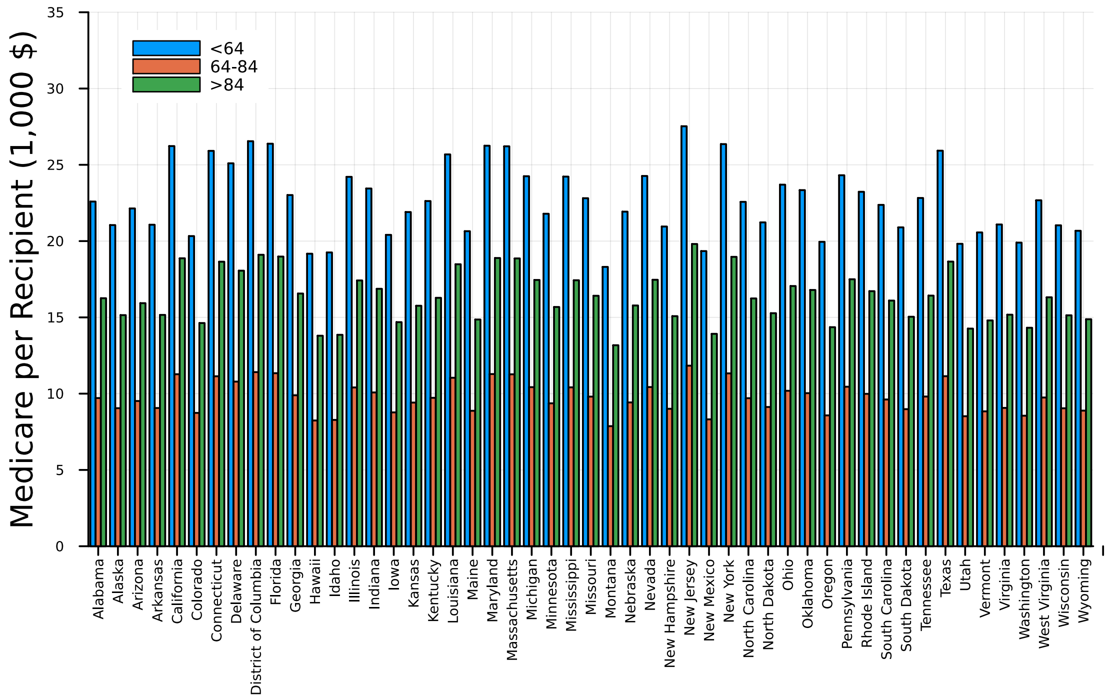

Figure 48: Average Medicare per Enrollee Spending in 2016 for three different age groups. Source: Centers for Medicare & Medicaid Services and authors' computations.

Finally, to convert the public spending amounts into household cash values, we use an estimate from Finkelstein and McKnight (2008) who found that eligibility for Medicare reduced the sume of out of pocket health expenditure plus private insurance spending by 82 cents for every dollar of Medicare spending. Thus, we set the cash value of Medicare receipt equal to 82% of per enrollee Medicare expenditure.

I Reweighting State Income Distributions

Because state income distributions are different, federal taxes and transfers are more progressive in poorer states. As we want to identify pure state policy differences, we, therefore, adjust the ASEC weights so that state income distributions are normalized.

We proceed as follows: In our ASEC baseline sample, we sort households i into gross income deciles using the

[92]The data we work with are "Health Expenditures by State of Residence", available here: https://www.cms.gov/data-research/statistics-trends-and-reports/national-health-expenditure-data/state-residence. They are a comprehensive measure of public Medicare spending, covering all health care goods and services consumed under Medicare Parts A to D.

original ASEC weights, w_i and compute the weight share of each decile W_j with $j = 1:10$

$$\begin{aligned} W_1 &= \frac{\sum_i I_{\{y_i \le Y_1\}} w_i}{\sum_i w_i} \\ W_2 &= \frac{\sum_i I_{\{y_i > Y_1 \text{ and } y_i \le Y_2\}} w_i}{\sum_i w_i} \\ &... \end{aligned}$$

where Y_j denotes income decile values and I is an indicator function. Note that, by construction, $\sum_j W_j = 1$.

Next, we compute the same weight shares for each state, W_j^s using the same (national) income decile values:

$$\begin{aligned} W_1^s &= \frac{\sum_i I_{\{y_i \le Y_1 \text{ and } i \in s\}} w_i}{\sum_i w_i} \\ W_2^s &= \frac{\sum_i I_{\{y_i > Y_1 \text{ and } y_i \le Y_1 \text{ and } i \in s\}} w_i}{\sum_i w_i} \\ &... \end{aligned}$$

Now, we construct new weights for all households in state s with $y_i \le Y_1$ using

$$w_i^{new} = \frac{W1}{W1^s} w_i$$

and proceed analogously for households with different incomes.

Note that

$$\begin{aligned} \sum_i I_{\{y_i \le Y_1 \text{ and } i \in s\}} w_i^{new} &= \frac{W_1}{W_1^s} \sum_i I_{\{y_i \le Y_1 \text{ and } i \in s\}} w_i \\ &= \frac{W_1}{W_1^s} W_1^s \sum_i I_{i \in s} w_i \\ &= W_1 \sum_i I_{i \in s} w_i \end{aligned}$$

and thus

$$\begin{aligned} \sum_i I_{\{i \in s\}} w_i^{new} &= (W_1 ... + W_{10}) \sum_i I_{i \in s} w_i \\ &= \sum_i I_{i \in s} w_i \end{aligned}$$

so, at the national and state level, the sum of the new weights equals the sum of the old (ASEC) weights.

Figure 49 illustrates the effect of this reweighting procedure on state income distributions. Using the new weights aligns them closely to the national distribution.

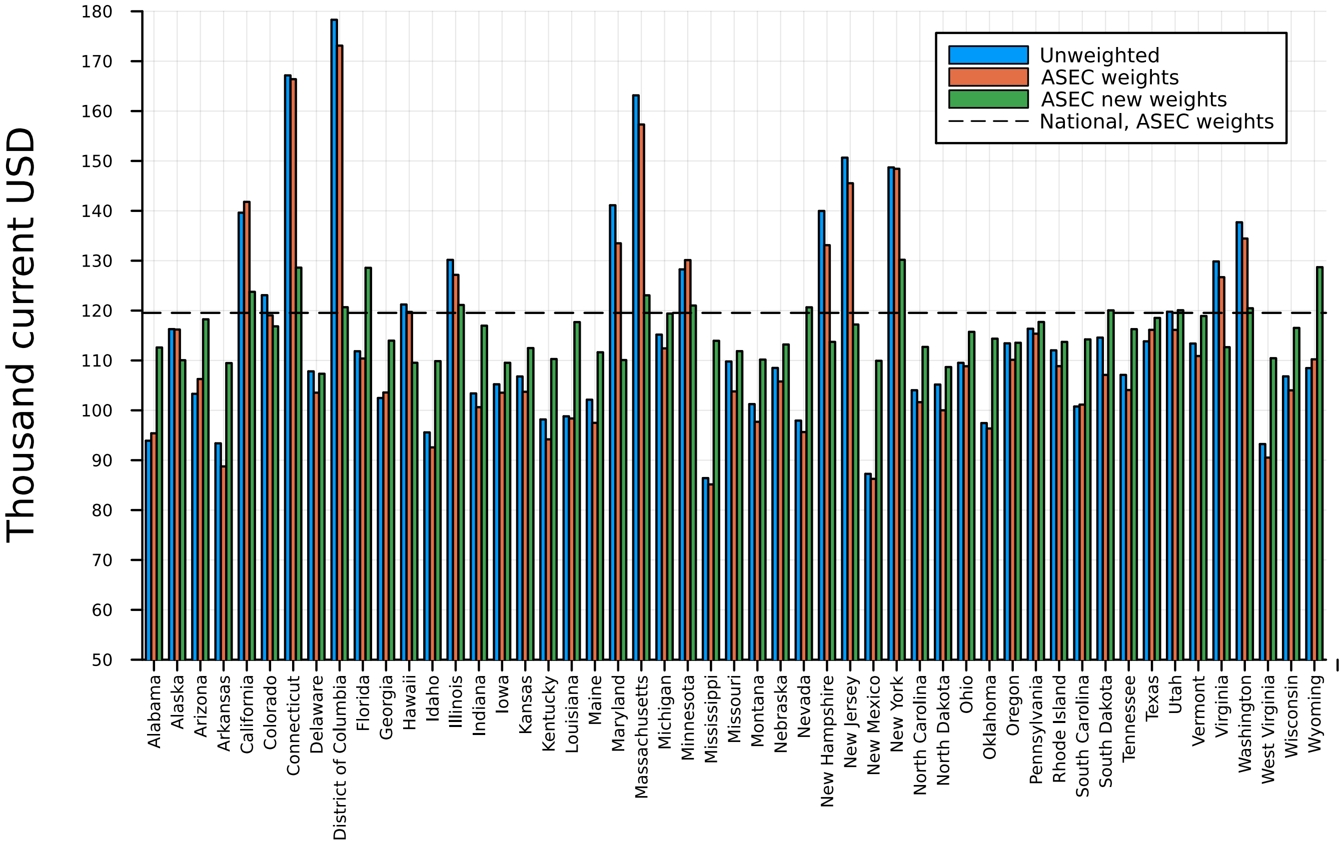

Figure 49: Means of ASEC sample household income distributions using different (no) weights (2015/2016).

J More details on changes over time in state tax and transfer progressivity

Table 9 reports average τ^s estimates and the standard deviation of those estimates across states for our three sample periods. The first row labelled "Baseline" corresponds to the τ^s values discussed in Section 3.4. The remainder of the table reports τ estimates using (i) all state taxes (but no transfers), (ii) only state income taxes, (iii) only state property taxes, (iv) only sales and excise taxes, (v) all state transfers (but no taxes), (vi) only unemployment insurance benefits, (v) only the state component of Medicaid, (vi) only other state transfers (Workers Compensation, TANF and the Alaska Permanent Fund Dividends). The table documents that larger Unemployment Insurance benefits were the main factor boosting average state progressivity in 2010/11. It also documents that Medicaid pushed up both average state progressivity and dispersion in state progressivity between 2010/11 and 2015/16.

Figure 50 provides more details on time variation at the state level. It plots estimated progressivity in 2005/2006 on the horizontal axis against estimated progressivity in 2010/2011 (green) and in 2015/2016 (blue) on the vertical axis and shows their rank correlation coefficient. All dots (except for Alaska) are close to the 45 degree line and the rank correlation is high, indicating our estimates capture persistent policy differences between state governments.

	2005/06		2010/11		2015/16		Correlations	
	mean	stdev	mean	stdev	mean	stdev	2005/06–2010/11	2010/11–2015/16
Baseline	-0.002	0.016	0.003	0.017	-0.003	0.020	0.85	0.82
Taxes	-0.030	0.012	-0.037	0.015	-0.035	0.015	0.82	0.88
Income	0.010	0.007	0.011	0.008	0.012	0.008	0.93	0.91
Property	-0.018	0.009	-0.023	0.013	-0.022	0.012	0.89	0.94
Sales and Excise	-0.021	0.004	-0.023	0.005	-0.022	0.005	0.87	0.92
Transfers	0.024	0.012	0.034	0.012	0.027	0.014	0.78	0.75
Unemployment Insurance	0.007	0.003	0.018	0.007	0.005	0.002	0.51	0.25
Medicaid	0.014	0.006	0.013	0.005	0.019	0.008	0.81	0.80
Other	0.004	0.007	0.004	0.007	0.003	0.009	0.92	0.93

Table 9: Unweighted estimates of state tax and transfer progressivity. "Baseline" refers to τ^s (see Section 3.4). As the estimated tax function is non-linear, component estimates do not exactly add up to aggregate estimates. "Other" transfers are Workers Compensation, TANF and the Alaska Permanent Fund Dividend (APFD). "Correlations" show the Pearson correlation coefficient computed for progressivity between the printed years.

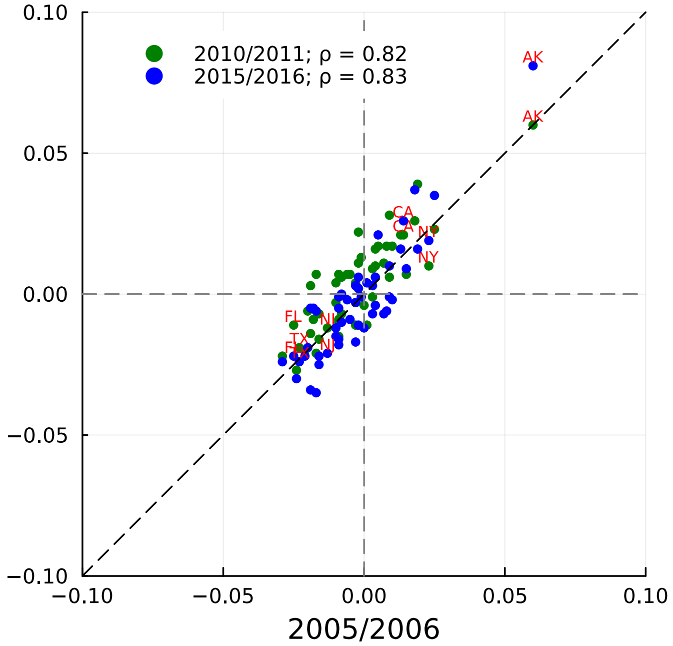

Figure 50: Time Variation in State Progressivity, τ^s. Estimate uses all state taxes and transfers (see Section 3.4). ρ is the Spearman's rank correlation coefficient for 2005/2006-2010/2011 and 2005/2006-2015/2016.

K Tax rates and tax progressivity with Medicare and Medicaid valued at full cost

In this extension, we assume that the cash value to Medicare and Medicaid enrollees is equal to full administrative expenditure per enrollee on those programs. Recall that in our baseline measurement we assumed that cash values were 82% of spending for Medicare and 40% of spending for Medicaid. Thus, the value of transfers relative to income becomes much larger for low income households in this extension, as shown in Figure 51. Figure 52 shows average state tax and transfer rates by state once we include Medicaid valued at the amount spent. Relative to our baseline, this alternative assumption does not change net tax rates by much, nor does it have much impact on the

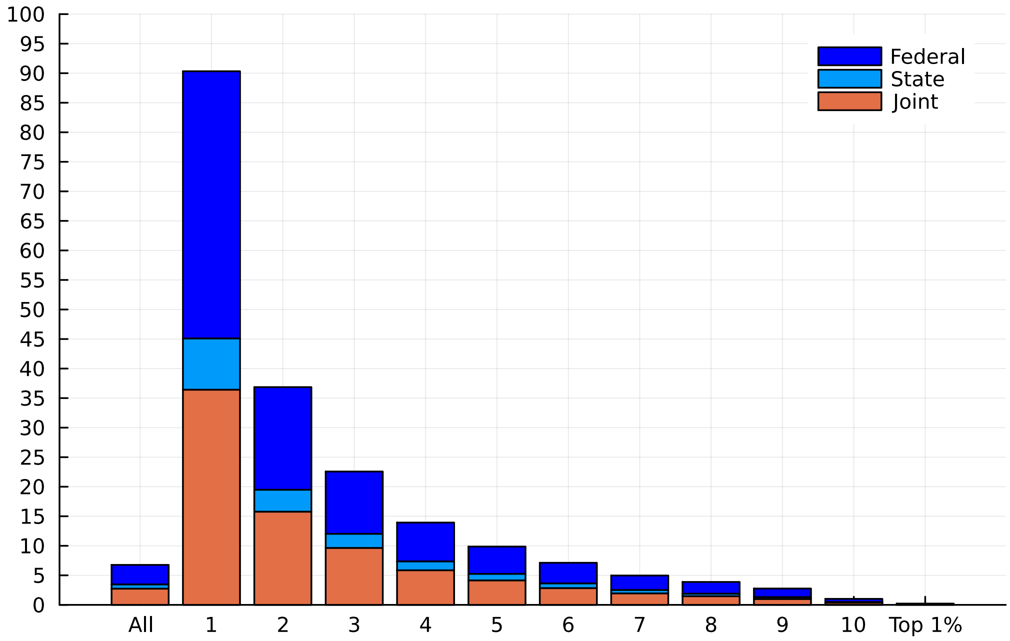

Figure 51: Average transfer rates 2015/2016 with Medicare and Medicaid at full cost. See notes to Figure 1.

cross state ranking of net tax rates. Figure 53 does the same thing for state tax progressivity.

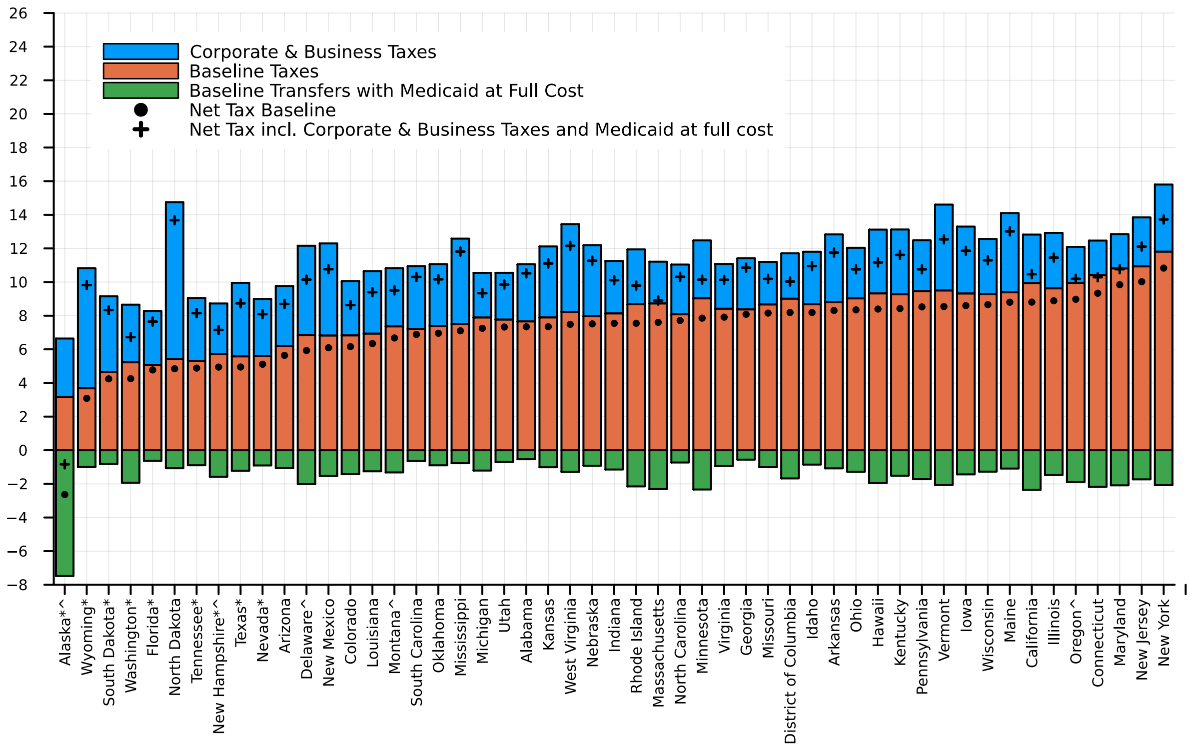

Figure 52: Average tax and transfer rates by state, including transfers from Medicaid at full cost (instead of cash values). Baseline taxes includes income, excise, sales and property taxes. Corporate & Business Taxes include corporate income and business taxes. ASEC baseline sample, 2015/2016.

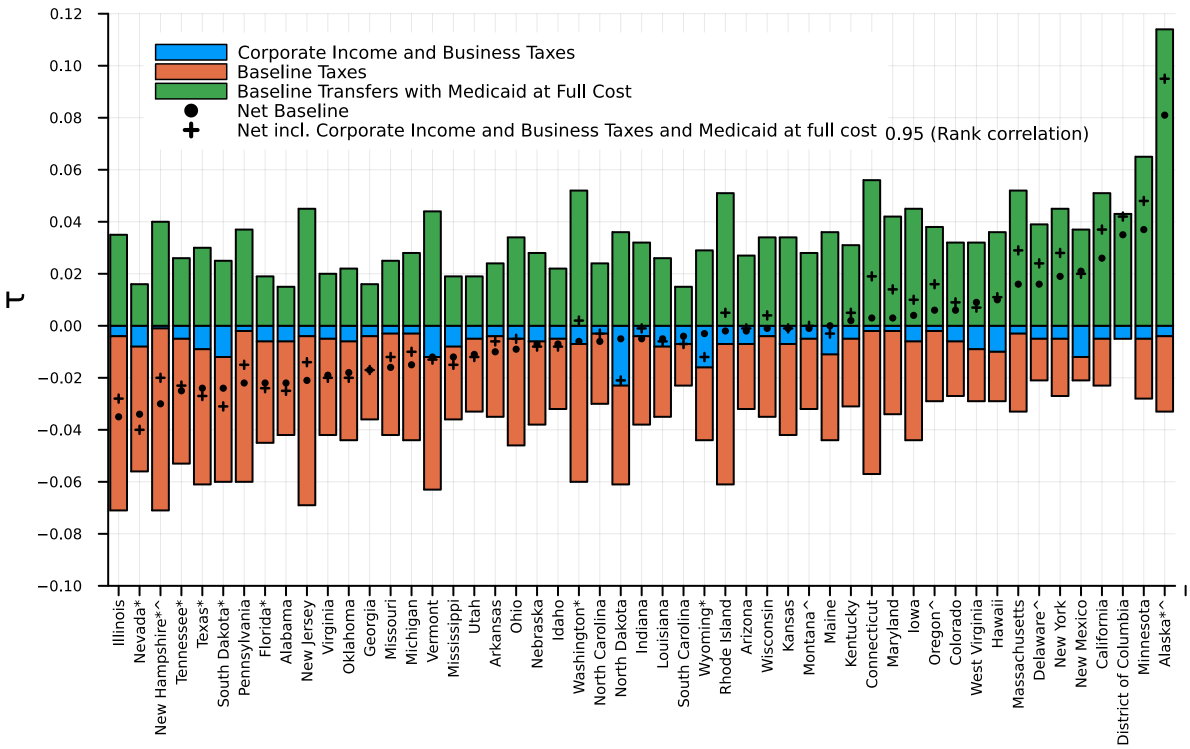

Figure 53: State τ^s decomposition. The plot shows estimates for progressivity induced by each of the state level taxes and transfers indicated in the legend, considering one tax at a time, using household weights constructed as described in Appendix I. The black dots report overall state progressivity as reported in Figures 16 and 17. Estimates are for 2015/2016.

L Corporate Income Taxes

Corporate income taxes are levied on profits of incorporated businesses, and thus on shareholders' dividends. The burden of corporate income taxes does, however, also partially fall on labor income to the extent that firms share rents with workers. Serrato and Zidar (2016) estimate the incidence of state corporate taxes on workers to be around 30-35%. Kline, Petkova, Williams, and Zidar (2019) examine the impact on wages of rents generated by successful approval of an economically valuable patent in U.S. firms. They find that workers capture roughly 40 cents of every dollar of patent-induced rent. Lamadon, Mogstad, and Setzler (2022) create a matched employer-employee data combining all U.S. businesses and workers with tax records for the period between 2001 and 2015. Using several different specifications and measures, they estimate that nearly half of firm-level rents are shared with workers. Dobridge, Landefeld, and Mortenson (2021) create a matched data set that links the universe of workers' W-2 forms with the tax returns of public and private corporations. In their preferred specification, workers captured 80 percent of the firm-level income generated by the Domestic Production Activities Deduction (a corporate tax reduction). Based on these findings, in what follows, we assume that the labor share of the tax incidence is 50%, an average between these various estimates.

There is also evidence that the sharing is far from equal across workers. Dobridge, Landefeld, and Mortenson (2021, Figure IX) finds that 60% of the income generated by the tax reform goes to the top 1% of workers ranked by within-firm compensation and to the owner, and another 35% to workers between the 75th and the 99th percentile. Kline, Petkova, Williams, and Zidar (2019) report a similar finding, i.e. no effect below the first quartile. Based on these results we assume that, of the total incidence on labor, 60% is concentrated in the top 1%, 40% on workers between the 75th and the 99th percentile, while workers below the top quartile are insulated from the corporate tax.

L.1 Federal Corporate Taxes

Operationally, let T_t^{corp} be the total federal corporate tax revenues in year t, W_t be the total wage bill, and $Wshare_t\left(q\right)$ be the share of total wage bill in earnings quantile q. Then, the effective corporate tax rate paid on labor income by workers in the top percentile $q = 100$ is

$$t_{q=100,t}^{corp-lab} = \frac{0.5 \times 0.6 \times T_t}{W_t \times Wshare_t\left(100\right)}$$

For workers in percentiles $q \in [75, 99]$:

$$t_{q\in[75,99],t}^{corp-lab} = \frac{0.5 \times 0.4 \times T_t}{W_t \times Wshare_t\left(75 - 99\right)}$$

For workers below the $q = 75$, as explained

$$t_{q\in[1,74],t}^{corp-lab} = 0.$$

The other half of corporate taxation falls directly on profits. We distribute it across the population proportionately to their share of dividend income. Let D_t be the total dividends, and $Dshare_t\left(q\right)$ be the share of total dividend income in earnings quantile q. Then the effective corporate tax rate paid on dividend income by workers in percentile q is

$$t_{q,t}^{corp-div} = \frac{0.5 \times T_t}{D_t \times Dshare_t\left(q\right)}$$

L.2 State Corporate Taxes

We assume that the pass-through from state corporate taxes on labor income is local, i.e. it falls entirely on workers of that state.[93] The approach is exactly the same as for the calculation at the federal level, with the obvious difference that we use corporate tax revenues T_t^{corp}, wage bill W_t and wage bill shares $Wshare_t(q)$ at the state level.[94]

We also assume the pass-through on capital income is national, i.e. additional state taxes paid by the firm in the states where it operates are all aggregated together across states and, collectively, reduce the dividends paid by the firm to all its shareholders nationally.

[93] Put differently, large firms operating in different states do not share the cost/benefit of a change in a single state corporate tax rate across all other firm employees working in other states.

[94] The quantile q is always calculated at the national level.

L.3 Imputation

To impute federal and state corporate taxes paid using the approached detailed above, we use data on federal corporate tax collections from the historical tables of the Office of Management and Budget[95], data on state-level corporate tax revenue from the Census of State and Local Governments, data on state wages and salaries from the Bureau of Economic Analysis (BEA) as well dividend income from the ASEC dataset (after augmenting it with the IRS-SOI data).[96]

To align the administrative amount of corporate tax revenue we allocate into the ASEC dataset with the aggregate incomes reported there, we divide labor income reported in the ASEC by the corresponding total reported in the BEA and use it to scale the amount of corporate tax revenue we allocate. For the federal taxes and the state taxes allocated on dividend income, we use total salaries and wages in the ASEC and BEA. For state taxes allocated on labor income, we use each state's ASEC and BEA wages and salaries.

Next, we compute per household tax amounts (again, using state populations for state taxes on labor) as well as mean household dividend income in our augmented ASEC dataset. Finally, we assign the federal and state corporate income tax due to profit incidence by multiplying the ratio of a household's dividend income relative to the mean dividend income with the corresponding per household tax amount. We proceed analogously for the labor incidence using the ratio of a household's labor income relative to mean labor income in the respective income percentile.

M Business Taxes

As illustrated in appendix A, businesses pay a variety of state and local taxes, and these taxes are passed on to households either through lower profits for their owners, or lower wages for workers, or higher prices for consumers. Our main data source for state-level business tax revenues is a series of reports called "Total state and local business taxes, State-by-state estimates" (available since fiscal year 2004) prepared by Ernst & Young LLP in conjunction with the Council On State Taxation and the State Tax Research Institute (Ernst and Young, 2016). These reports contain, for each state and year, estimates of state tax revenue by source (households vs. businesses) based on data from the Census of State and Local Government Finance (CSLG). They provide annual revenues for seven types of state and local taxes: property tax, sales tax, excise tax including public utilities and insurance, corporate income tax, unemployment insurance tax, individual income tax on business income, license and other taxes (such as documentary and stock transfer taxes, severance taxes, and local gross receipts taxes).

We abstract from the individual income tax on business income, the unemployment insurance tax, and the corporate income tax because we already account for them in our previous calculations on the state personal income taxes and corporate income taxes, respectively. In addition, we noted that these reports assume that all revenue from public utilities and insurance excise taxes falls to businesses. Since in our computation of household consumption taxes we have already included 2/3 of public utility taxes and all insurance taxes, we subtract these amounts to avoid double

[95] See here: https://obamawhitehouse.archives.gov/omb/budget/Historicals.

[96] Note that dividend income is self-reported in ASEC, while ordinary dividend income is a separate line item in the IRS-SOI tables.

counting. We also subtract amusement taxes and assume they are all paid by households, so we include them in our consumption tax calculation. We group the remaining tax revenues into two broad categories: (1) *Intermediate taxes*, which include sales taxes, excise taxes, and license and other taxes. In other words, all taxes on intermediate inputs. (2) *Property taxes*, which only includes the property tax.

To compute the incidence of these two taxes on households, we follow the strategy outlined in the most recent version of the "Minnesota Tax Incidence Study" (Minnesota Department of Revenue: Tax Research Division, 2024).

Intermediate goods tax Since taxes on short-lived intermediate business inputs directly raise the cost of production, we assume that their incidence is shifted forward either to labor via lower wages or to consumers via higher prices, depending on whether the business produces a tradable or a non-tradable good, respectively.

Let $R^m_{s,t}$ denote the amount of tax revenues that state s raises in year t through taxes on intermediates m. Let $\alpha^{tr}_{s,t}$ be the share of the tax revenues paid by businesses which sell tradable goods. For these goods, the price is determined nationally and cannot be raised to accommodate the local tax. As a result, $\alpha^{tr}_{s,t} R^m_{s,t}$ falls on labor.

To estimate $\alpha^{tr}_{s,t}$, we make the assumption that the ratio of expenditures in intermediate inputs to output in tradable and non-tradable sectors is the same. Then, we can proxy $\alpha^{tr}_{s,t}$ with the share of state s output produced by the tradable sector. Namely, we combine data on GDP by state and industry from the BEA[97] with the categorization proposed by Delgado, Bryden, and Zyontz (2014) which splits industries based on whether they produce tradable or non-tradable goods and services. Since all labor is local, we allocate this tax burden proportionately to labor income $Y^L_{s,t}$ in the state. Estimates of total labor income by state are obtained from the BEA.[98]

Thus, the effective tax rate on local labor is:

$$t^{m_L}_{s,t} = \frac{\alpha^{tr}_{s,t} R^m_{s,t}}{Y^L_{s,t}} \tag{20}$$

The tax rate $t^{m_L}_{s,t}$ is applied proportionately to labor income to each household who resides in state s in year t in our dataset.

Businesses which sell non-tradable goods are instead assumed to pass the tax on to consumers. Let $C^{ntr}_{s,t}$ be total spending on non-tradables in state s in year t. We estimate of $C^{ntr}_{s,t}$ as personal consumption expenditures in state s and year t net of what is spent on "Goods" (i.e. tradables) using BEA data.[99]

The effective tax rate on non-tradable spending in state s and year t is

$$t^{m_C}_{s,t} = \frac{(1-\alpha^{tr}_{s,t}) R^m_{s,t}}{C^{ntr}_{s,t}} \tag{21}$$

After merging CEX spending variables into the ASEC dataset as described and splitting total spending into tradable and non-tradable, we apply this tax rate proportionately to non-tradable spending for each household in our dataset.

[97] NIPA Table SAGDP2N. See https://www.bea.gov/data/gdp/gdp-state.

[98] NIPA Table CAINC5N on Personal Income by State (line Wages and Salaries). See https://www.bea.gov/data/income-saving/personal-income-by-state.

[99] NIPA Table SAPCE4 on personal spending by state and industry. See https://www.bea.gov/data/consumer-spending/state.

Property tax Let $R^h_{s,t}$ be the tax revenue raised from non-residential property taxes, i.e. property taxes paid by businesses in state s and year t. This estimate from Ernst and Young (2016) also includes taxes paid by individual landlords on rented properties. Because we have already accounted for the share of these taxes passed on to renters (see appendix F.2 and F.3) we subtract this share from $R^h_{s,t}$ in all the calculations that follow. Let $\hat{R}^h_{s,t}$ be the adjusted tax revenue.

Let $\alpha^{land}_{s,t}$ be the land share of non-residential property values. Since we are not aware of any estimate of the land share for businesses, we use estimates of the land shares for residential housing by state from Davis, Larson, Oliner, and Shui (2021) under the assumption that the two land shares are the same. We assume that the land share of business property taxes falls on owners proportionately to business income which we use as a proxy for rental income.[100] Let $Y^B_{s,t}$ be total business income in state s and year t, estimated from BEA data.[101]

The effective property tax rate that falls on business owners is:

$$t^{h_B}_{s,t} = \frac{\alpha^{land}_{s,t}\hat{R}^h_{s,t}}{Y^B_{s,t}} \tag{22}$$

Next, we apply this tax rate proportionately to business plus farm income of each household residing in state s and year t in our dataset.

The residual $\left(1-\alpha^{land}_{s,t}\right)\hat{R}^h_{s,t}$ is treated as we did for revenues from taxes on intermediate inputs, i.e. we split it between the tradable share falling on workers and the non-tradable share falling on consumers. Respectively,

$$t^{h_L}_{s,t} = \frac{\alpha^{tr}_{s,t}\left(1-\alpha^{land}_{s,t}\right)\hat{R}^h_{s,t}}{Y^L_{s,t}} \tag{23}$$

and

$$t^{h_C}_{s,t} = \frac{\left(1-\alpha^{tr}_{s,t}\right)\left(1-\alpha^{land}_{s,t}\right)\hat{R}^h_{s,t}}{C^{ntr}_{s,t}} \tag{24}$$

Next, we apply both $t^{h_L}_{s,t}$ and $t^{h_C}_{s,t}$ to labor income and non-tradable spending for each household in our sample, as explained above for the intermediate goods tax.

Figure 54 shows the effective tax rates for each component of business taxes, constructed as explained above, in every state for the entire ASEC dataset (in 2015/2016).

[100] We use business income for two reasons. First, the ASEC rental income variable includes income from royalties, trust and estates. Second, the SOI data, which we use for the replacement of high-income ASEC households, do not report rental income separately. To construct a measure for business income which is consistent between ASEC and SOI, we sum ASEC business and farm income as Larrimore, Mortenson, and Splinter (2019) show that those two variables are similar to SOI business income.

[101] NIPA Table CAINC5N on Personal Income by State (line Proprietor's Income).

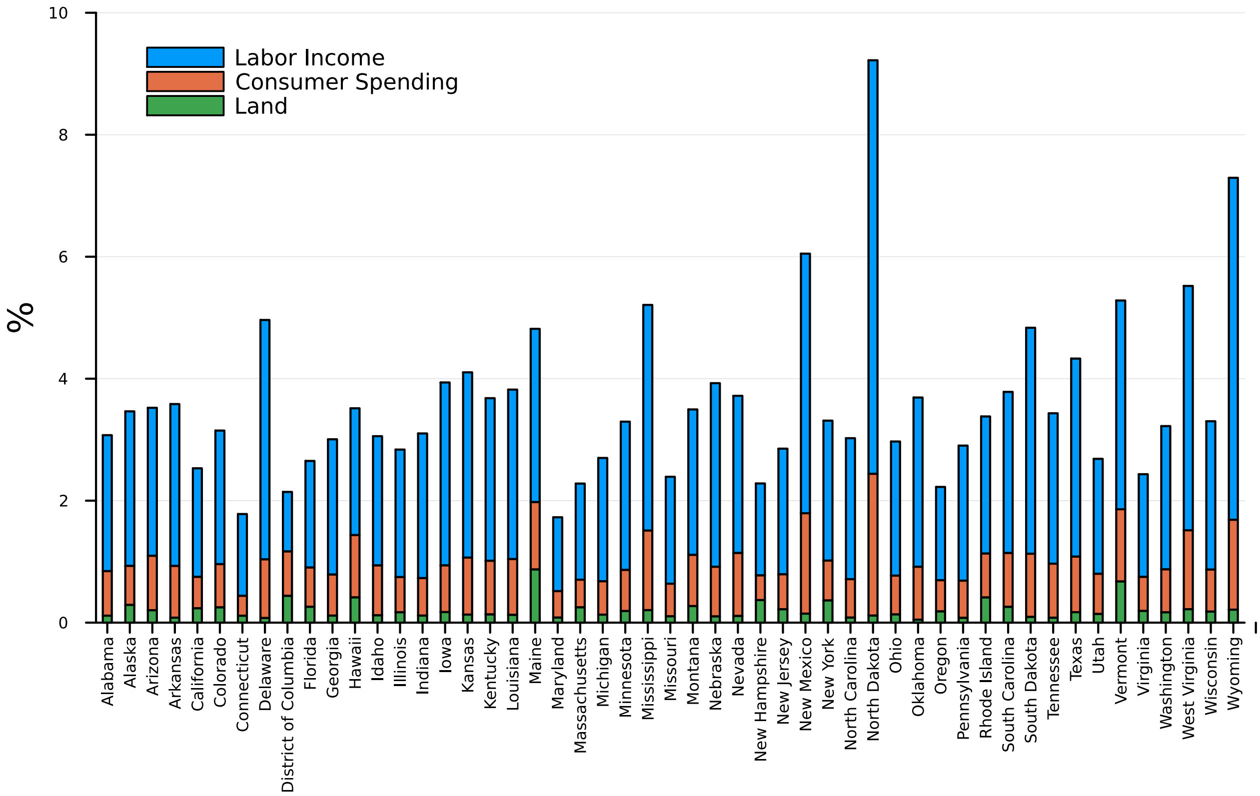

Figure 54: Effective business tax rates by state (2015/2016). Computed by dividing total state household gross income by total taxes paid using the entire ASEC dataset.

N Federal, State, and Local Spending

N.1 Federal Spending

We obtain data on federal Spending from NIPA Table 3.16. Government Current Expenditures by Function for 2006, 2011, and 2016.

In our measure of spending we include: General public service (line 43), except for Interest payments because they are not an expenditure that is valued by households, National defense (48), Public order and safety (49), Economic Affairs, e.g. Transportation (54), Housing and community services (67), Recreation and culture (69), Education (70), with Elementary and secondary education spending being allocated proportional to the number of school-age children in the household.

We exclude Income security (e.g., UI and other welfare an social insurance benefits) and Health (e.g., Medicare) because they are already part of our transfer calculations.

N.2 State and Local Spending

We obtain data on state and local spending from the "Census of Governments" dataset of the Census Bureau for years 2006, 2011, and 2016. Specifically, we base our calculations on Table 1. State and Local Government Finances by Level of Government and by State. The state government data in this table are from a survey of all state governments and are not subject to sampling error. The local government data in this table are, instead, from a sample of local governments, and as such, are subject to sampling variability.

For 2006, Figure 55 shows all total state and local spending as a share of state GDP, by major components. However, we only include a subset of these expenditures in our calculations

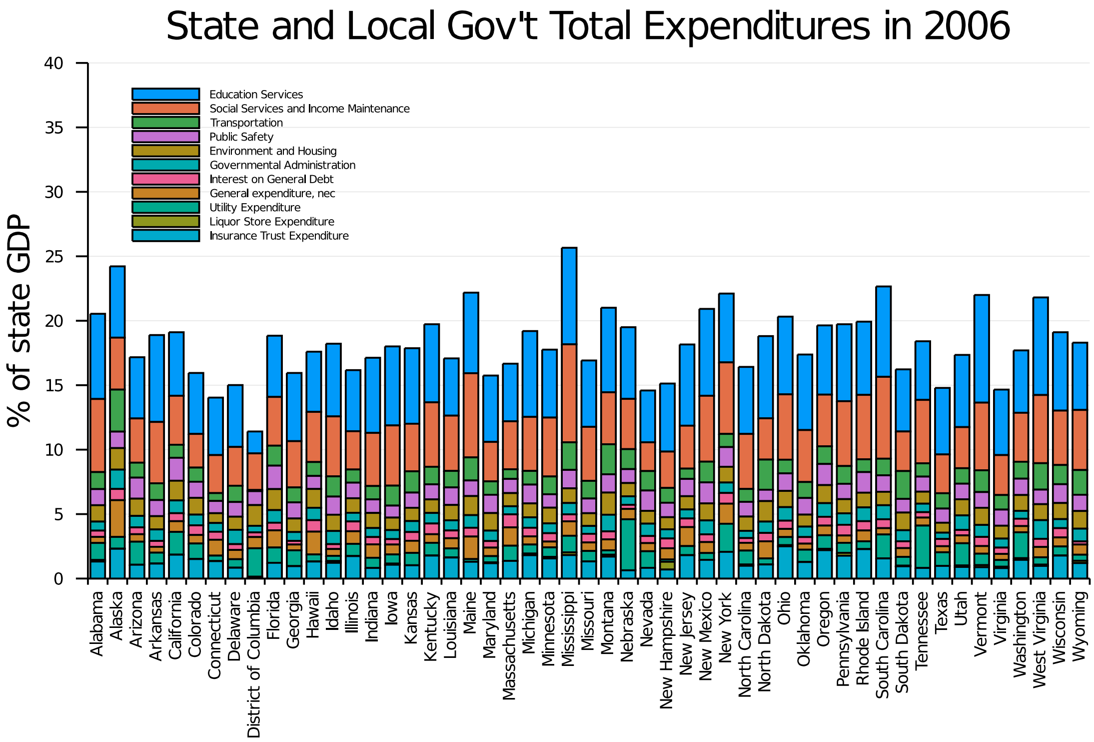

Figure 55: State and local total spending scaled by GDP

Education. We include all components of spending: Higher Education (line 71), Elementary and Secondary Education (73), Other Education (75), and Library (76). From these, we subtract revenues through charges for Institutions of higher education (25) and School lunch sales (26). As explained in the main text, Elementary and Secondary education net of charges for school lunches are assigned to households based on the number of kids of school age.

Social services and income maintenance. We include spending on Hospitals (line 81) net of charges (27), Health (83), Employment security administration (84), and Veterans' services (85). We exclude all Public welfare because all these expenditures are already included in our measures of transfers.

Transportation. We include all components: Highways (line 86) net of charges (28), Airports (88) net of charges (29), Parking facilities (89) net of charges (30), Sea and inland port facilities (90) net of charges (31).

Public safety. We include all components: Police protection (line 92), Fire protection (93), Correction (94), Protective inspection and regulation (96).

Environment and housing. We include all items: Natural resources (line 97) net of charges (32), Parks and recreation (99) net of charges (33), Housing and community development (101) net of charges (34), Sewerage (102) net of charges (35), Solid waste management (104) net of charges (36).

Governmental administration. We include all items: Financial administration (line 106), Judicial and legal (107), General public buildings (108), Other governmental administration (109).

General expenditures. We include Miscellaneous commercial activities (line 111), but exclude a component called Other and unallocable.

Utility expenditure. We include all items: Water supply (line 115) net of charges (44), Electric power (116) net of charges (45), Gas supply (117) net of charges (46), Transit (118) net of charges (47).

From all these items, we exclude the capital outlays component which is always reported separately.

Finally, from our measure of net spending we exclude: (i) All taxes, because they are already included in our calculations, (ii) Liquor store revenue and expenditure because they are already part of our consumption taxes, (iii) Insurance trust revenue and expenditure because we have already included them in our tax and transfer calculations, (iv) Miscellaneous general revenue because it includes revenues from interests on assets and sales of properties, and (v) Interest on General Debt because it is a form of spending that does not generate any value to households.

Figure 56 shows this measure of state and local spending on public goods and services scaled per state resident for our sample years.[102]

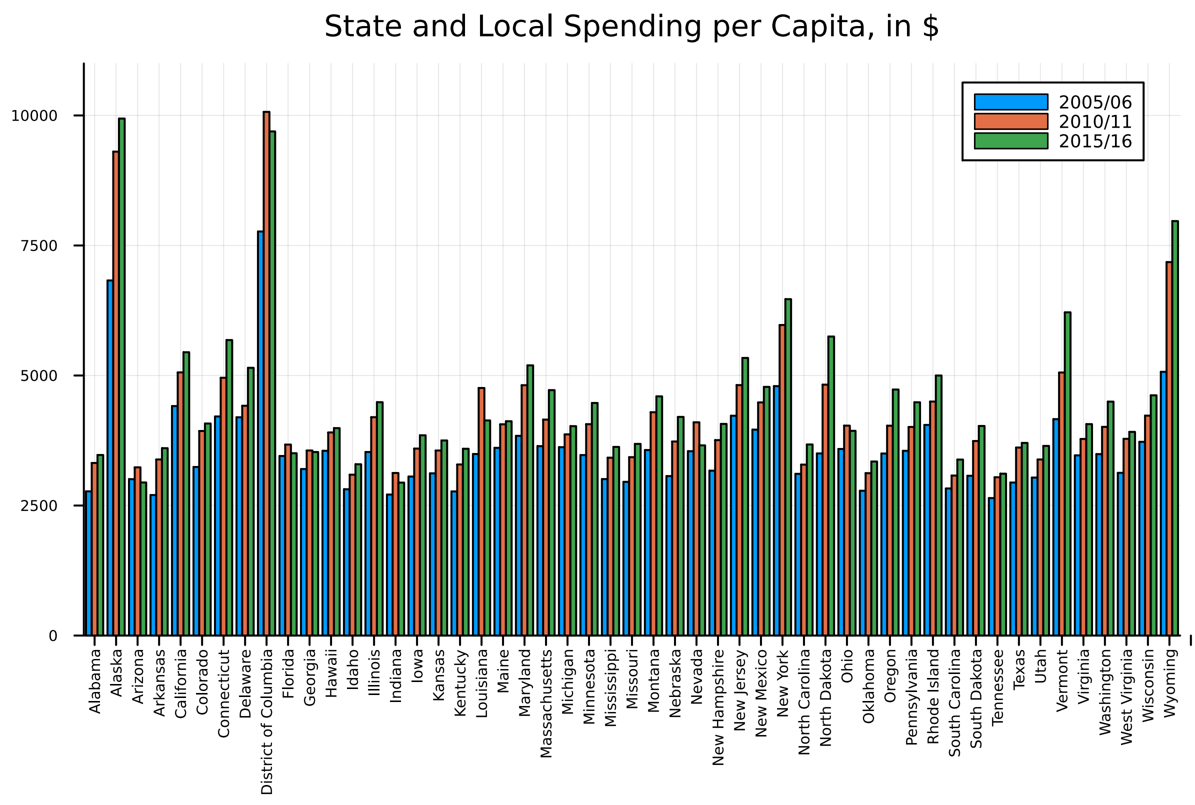

Figure 56: State and local spending on public goods and services per state resident.

O Progressivity Estimates for General Use

Main points to address: which function/estimation has which strengths/weaknesses and is suitable for what kind of applications?

[102]Population data are from the Census Bureau.

Some specific questions to answer:

1. How did we compute scale invariant lambdas? Jon's note
2. What is the HSV + T and why/when is it preferable? How is it estimated?
3. What is the point of using PPML (Koenig)? When is it better?

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