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ABSTRACT

Combining a variety of survey and administrative data, this paper measures the progressivity of taxes and transfers at the U.S. federal level and separately for each state. The findings are as follows. (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 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) Regressive states are concentrated in the South and attract more inter-state net migration, especially of high-income migrants. (vi) State progressivity has remained broadly stable between 2005 and 2016. (vii) Incorporating corporate income and business taxes decreases average state progressivity but increases federal progressivity. (viii) Including spending on public goods and services as a transfer has a large positive impact on measured progressivity.

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A Data repository is available at https://github.com/jo-fleck/federal_state_progressivity

1 Introduction

Rising income inequality in the United States and other countries has rekindled interest in using government redistribution through taxes and transfers to reduce disparities. 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 percent of GDP between 2010 and 2023, compared with 8.0 percent for federal personal income taxes and 6.4 percent for federal payroll taxes.[1] Moreover, there is large variation across U.S. states in the level of state and local tax revenue, the choice of tax base, and 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 the progressivity of taxes and transfers at the state and local level and contrasts it with 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 some 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 working age households as the unit of analysis and measure redistribution in terms of current taxes paid and transfers received as a function of current household income over the period of one calendar year. For short, we label the progressivity of the tax and transfer system simply as "tax progressivity." We approximate the tax and transfer system using a set of tractable functions that allow progressivity comparisons across time and locations. These functions are of intrinsic interest as a stand-in for the fiscal system in heterogeneous agent models.

Another 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. Specifically, we include all taxes levied directly on households: income taxes, property taxes, and consumption (sales and excise) taxes. On the transfer side, we include a comprehensive set of programs, featuring both welfare (means-tested) and entitlement programs.[2] In extensions,

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

[2] Most welfare transfer programs embed a close link between benefit eligibility and current income. In contrast, Social Security entitlement benefits, such as Medicare, are linked to *lifetime* income.

we study additional taxes and transfers, which require stronger incidence assumptions.

Our primary data source is the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS). We supplement it with a range of additional data sets, including the state-level tables of the Internal Revenue Service's (IRS) Statistics of Income (SOI), the Consumer Expenditure Survey (CEX), the American Community Survey (ACS), and the Census of State and Local Governments (CSLG).

In the ASEC micro data, state income taxes for each household are imputed by 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 derived from 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 landlords pass through to renters. Property taxes are typically set at the local level, and some local governments also raise income and sales taxes. In our analysis, we include these local taxes within each state, aggregate them into our measure of state tax progressivity and use the terms ″state and local″ and ″state″ interchangeably.

Research on poverty in the U.S. shows that the social safety net is geographically fragmented as states and local governments set parameters determining the accessibility and generosity of many transfer programs. For Medicaid, which is the largest state-run transfer program, we use administrative data on enrollment and spending by state and by household characteristics to impute benefit values to enrollees. To address the concern that other transfers may be underreported in the ASEC survey, we use Congressional Budget Office (CBO) imputations that are designed to correct for under-reporting in other transfer variables.

We partition the comprehensive set of household transfers in our dataset into those provided by the federal government, those provided by state governments and those provided by jointly by both levels of government. For joint transfers, we use federal versus state funding shares to apportion benefits received into federal and state components. This allows us to separate the progressivity of federal versus state transfers and to quantify cross-state generosity differences.

One challenge in measuring income and taxes at the top of the household income distribution is that the ASEC income and tax variables are top-coded. In addition, realized capital gains are an important source of income at the very top, but these are not available in ASEC for most of the years we study. We therefore use SOI state-level data to impute incomes 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 and tax progressivity at the state level. This extension requires making assumptions on the incidence of these taxes. In a second extension, we broaden our transfer measure by including estimates of the transfer value of government spending on public goods and services. This extension also requires incidence assumptions. Our most comprehensive tax and transfer measure includes the bulk of state and local revenue and spending. Thus, we can provide estimates of state progressivity that reflect the totality of state-level fiscal policies.

The key findings from our 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 progressivity across U.S. states. Fourth, the proximate cause of this variation is the choice of tax base: states relying on sales, excise, and property taxes tend to have regressive tax 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. Sixth, while average state tax progressivity changed little, on net, between 2005 and 2016, changes in individual state policies – such as unemployment benefit extensions and Medicaid expansions – are visible in our state progressivity estimates. Seventh, households at all income levels who migrate from one state to another appear to be drawn to states with less progressive tax and transfer systems. But lower progressivity appears to be an especially powerful draw for very high income movers.

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. Pechman and Okner (1974) were the first to use U.S. micro data to study the effect of a large set of taxes, including federal, state and local taxes, on the distribution of disposable income. Suits (1977) proposed an index to measure the individual progressivity of each of these taxes. His measure is based on Lorenz curves and finds that personal income and corporate income taxes, as well as property taxes, are progressive, while sales and excise taxes, personal property taxes and payroll taxes are regressive.

Heathcote, Storesletten, and Violante (2017) 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), and Benabou (2002) – 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 measure with the ranking based on the Suits (1977) index. We also estimate a more flexible functional form for the tax and transfer system proposed by Ferriere, Grübener, Navarro, and Vardishvili (2023) and Boar and Midrigan (2022).

Splinter (2020), Heathcote, Storesletten, and Violante (2020), and Borella, Nardi, Pak, Russo, and Yang (2023) 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, has increased over recent decades. Heathcote, Storesletten, and Violante (2020) and Borella, Nardi, Pak, Russo, and Yang (2023), in contrast, estimate that federal progressivity has overall not changed much since the early 1980s. 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 Institute on Taxation and Economic Policy (ITEP) has provided well-known evidence on this topic. It publishes an annual report called "Who Pays?" (McIntyre, Denk, Francis, Gardner, Gomaa, Hsu, and Sims, 2003). The ITEP considers the distributional impact of a set of taxes similar to the one we use, and constructs a state-level "Tax Inequality Index," which loads heavily on the top marginal rate of state income taxes. However, their analysis excludes all transfers, and their methodology is proprietary. Still, we compare our progressivity ranking to their index.

Earlier related studies focus on a narrow subset of state taxes and omit transfers. For example, Scott and Triest (1993) measure the evolution of federal and state income tax progressivity after the federal tax reforms of the 1980s. Similarly, Sammartino and Francis (2016) find that federal and state income taxes are progressive, but state income taxes are less progressive than federal ones, and their progressivity varies across states. Gravelle (2007) measures property taxes at the state level and reports large variation in tax burdens across locations and households. Some studies include a richer set of state and local taxes—for instance, Baker, Janas, and Kueng (2020), who study how different taxes correlate within a jurisdiction and over time.

Cooper, Lutz, and Palumbo (2015) adopt a more comprehensive approach to measuring the redistributive effect of state taxes as they include income taxes, general sales taxes and a select excise tax (on motor fuels), as well as corporate income taxes. But they omit property taxes as well as most excise taxes and do not consider any transfers. Hoynes and Luttmer (2011) use data from the Panel Study of Income Dynamics (PSID) to calculate the insurance value and the redistributive value of state-level tax and transfer programs. However, they also abstract from property and excise taxes and consider only a small set of transfers. Kosar and Moffitt (2017) and Fleck and Simpson-Bell (2019) study differences in transfer payments and income taxes across states but focus only on individuals at or below the poverty line.

In contrast to these studies, we incorporate the broadest possible set of federal and state taxes and transfers, as we consider all taxes raised directly from households, including property taxes. In extensions, we also consider corporate income taxes and taxes collected from businesses. Moreover, we include a large set of cash and in-kind transfer programs, most notably Medicare and Medicaid, and carefully model geographic benefit heterogeneity. We also develop and apply a new methodology to control for the confounding effect of differences in state income distributions on estimated federal and state progressivity to ensure that our estimates isolate true cross-state differences in policy.

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. Section 3 introduces our measure of progressivity and provides estimates for federal and state taxes and transfers for the U.S. as a whole. Section 4 provides estimates for the three different sample years we study and investigates what drives the variation in progressivity. In Section 5, we present extended measures of state tax progressivity that also include corporate income and business taxes as well as the transfer value of state spending on public goods and services. 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 the population of each U.S. state, which is central to our analysis. Moreover, it contains a rich set of income, transfer and (imputed) tax variables. We focus on three two-year periods: 2005/06, 2010/11, and 2015/16.[3]

[3]We pool observations over adjacent years to increase sample size. Figure C1 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.

One limitation of the ASEC survey for measuring income received and taxes paid is that related variables are top-coded in the publicly available version. This is concerning because a small share of high income households accounts for a large share of total taxes paid. For example, the IRS's Statistics of Income (SOI) data indicate that in 2016, tax filers with Adjusted Gross Income (AGI) exceeding $500,000 accounted for only 0.87 percent of all tax returns but for 35.3 percent of federal income tax revenues.[4]

To address the top-coding issue, we supplement the ASEC data with income and tax data from the IRS-SOI state-level tables. These tables report average values for numerous income and tax components for different bins of the AGI distribution. We replace income and tax values for ASEC households with pre-government income exceeding $200,000 with the corresponding values from the SOI state-level tables, drawing from the SOI income bins in proportion to their respective shares of all tax returns.[5]

Income definition Our ASEC measure of gross pre-government income is similar to that of Heathcote, Storesletten, and Violante (2017). It includes pre-tax income from wages and salaries, business and professional practice, farming and cropping, interests and dividends, rents and royalties, and assistance from friends and relatives (private transfers). Our income measure for the synthetic SOI households is total income (IRS form 1040 line 9) minus unemployment compensation minus taxable social security income.[6] Realized capital gains are not available in the ASEC for our sample years, but they are included in measured income for our synthetic high income SOI households.[7] For households with wage income we add the employer-paid portion of payroll (FICA) taxes (which is identical to the employee-paid value) to our pre-government income measure.

Reported income in the ASEC and the SOI falls short of aggregate personal income as measured in the National Income and Product Accounts (NIPA). This shortfall is most pronounced for business income (see, for example, Rothbaum 2015, and Imboden, Voorheis, and Weber 2023). As we estimate *actual* net taxes paid across the *reported* income distribution, our reported tax rates will be too high if reported income is less than true income. Furthermore, if underreporting of income were especially severe at relatively high income levels, but our estimates for net taxes paid given reported income are correct, our reported tax rates for the rich, and thus

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

[5]We retain the ASEC measures for government transfers and the household-level ASEC weights. Appendix B provides more details on our SOI replacement approach.

[6]The SOI income measure misses non-taxable components of income, such as tax-exempt interest income.

[7]According to the IRS, in 2016, 86 percent 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.

our estimates for tax progressivity, would be too high. One possible remedy for this problem would be to posit a model for missing income and use it to inflate the income values reported in the ASEC and SOI data so as to match "true" income. Both Piketty, Saez, and Zucman (2018) and Auten and Splinter (2024) attempt such an exercise, subject to assumptions on how unreported income is distributed. For simplicity we have not pursued such adjustment.

Taxes For each household in our sample, we measure or impute estimates for a range of federal, state and local taxes. Federal taxes comprise federal income taxes, federal payroll taxes (both the employer and employee portions and the self-employment payroll tax) and federal excise taxes. In an extension, we also include federal corporate income taxes. State and local taxes comprise income taxes, property taxes, sales taxes, excise taxes and user charges.[8] In an extension, we include state-level corporate income taxes and taxes collected from businesses, such as property as well as sales and excise taxes (which apply to business purchases of goods and services).

The SOI data that we incorporate for high income households have several useful features for estimating taxes. First, the SOI tables report actual 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 and local income taxes and for property taxes paid.[9] We use this information to impute state and local income taxes and property taxes to our synthetic SOI households. Figure B1 in Appendix B.3 reports effective tax rates by state for SOI households with AGI between $500,000 and $1m in 2016.

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

Federal transfers 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 also include Social Security Old-Age Benefits, although these are quite small for our sample of working age households. Finally, we include Medicare, where we measure the value of the benefit for eligible households at 82 percent of state-specific spending per enrollee, following Finkelstein and McKnight (2008) and Hendren and Sprung-Keyser (2020).

[8]"Local" taxes include all taxes set at the sub-state level, including county, municipality, township, special district and school district taxes.

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

Two transfer programs – Medicaid and Temporary Assistance for Needy Families (TANF) – have both federal and state components, which we allocate to the two levels of government. Their generosity varies across states. Following Finkelstein, Hendren, and Luttmer (2019), we assume that the value of Medicaid to recipients is equal to 40 percent of administrative spending per enrollee.

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

In addition to our baseline set of transfers, we also report results for a broader transfer measure that includes estimates of federal, state and local per capita spending on public education and on publicly provided other goods and services. For this broader transfer measure we attribute a cash value of Medicare and Medicaid spending at 100 percent of their corresponding expenditures.

Sample Our unit of observation is the household. In our baseline analysis, we follow the same sample construction criteria as Heathcote, Storesletten, and Violante (2017) and select 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).[10]

Table 1 summarizes the federal versus state and local components of taxes and transfers, and reports their average values relative to average pre-government household income in 2015/16. As expected, 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 imputed by the Census Bureau (CB) tax model. While this model is similar to the TAXSIM model of the National Bureau of Economic Research, it also integrates confidential IRS and ASEC data to deliver accurate measures of some income components (such as capital gains) as well as tax credits (such

[10]For 2015/2016, this attachment requirement implies that we drop 13.8 percent of households in the 25-60 age range.

	Federal Taxes and Transfers	Sample	All	State & Local Taxes and Transfers	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, state and local taxes and transfers. The data shown refer to sample years 2015/2016 and have been computed using ASEC household weights. 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.

as the Earned Income Tax Credit (EITC) and Child Tax Credit), deductions, and exemptions.[11]

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 CB'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 CSLG, and allocate it proportionately to income across all state residents.[12]

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 percent and 1.45 percent, respectively, for both the employer and the employee, resulting in a total rate of 15.3 percent. These taxes apply to

[11]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.

[12]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.

wage income. Importantly, the Social Security tax applies to income only up to the OASDI limit ($118,500 in 2016) while the Medicare tax base is uncapped. A similar tax, with the same 15.3 percent total rate, applies to income from self-employment.

The CB 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 for wage and salary income for employees. We also add this same amount to the household pre-government income variable for employees. The total tax liability variable in the IRS-SOI state-level tables includes FICA taxes for the self-employed. However, these 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) 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 gross 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.

2.2 Sales and Excise Taxes

Households pay taxes on their consumption expenditures via sales and excise taxes. These are set mainly at the state and local level as the federal government levies excise taxes only on a small set of goods, including gasoline, alcohol, and tobacco.[13] Our strategy for imputing household-level sales and excise taxes is to multiply sales and excise tax rates specific to each good or service by household-level consumption expenditure on that good or service. This procedure requires two basic inputs – imputed consumption spending and tax rates.

Consumption spending We estimate household spending on different categories of goods and services as a function of household income. For each of our sample years, the Consumer Expenditure Survey (CEX) reports average household expenditure by category for different household income bins (Table 1203). The data refer to the U.S. as a whole. We impute con-

[13]We abstract from federal government taxes on imported goods via tariffs.

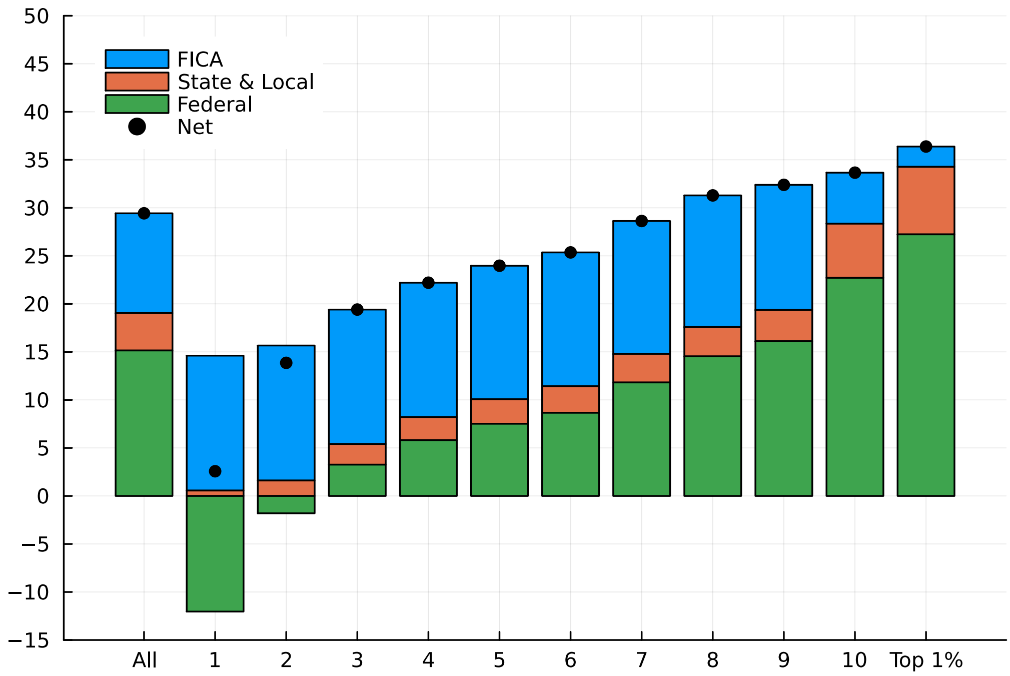

Figure 1: Average income tax rates (Federal, State & Local) and FICA tax rates for our ASEC sample, 2015/2016. Rates are plotted for all sample households, for 10 deciles of the household pre-government income distribution, and for the top 1 percent of households by income. For each bin, tax rates are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

sumption expenditure functions by linearly interpolating between the bin mean incomes. For income levels larger than the largest CEX mean income, we use a log-linear extrapolation. For incomes lower than the lowest CEX mean income, we use the lowest CEX mean income.[14]

For every good or service j we scale the consumption function so that when aggregated across all households in the full ASEC dataset, aggregate imputed expenditure on j equals NIPA expenditure on j. The motivation for this adjustment is that some components of spending are under-reported in the CEX relative to aggregate measures while others are over-reported (see Garner, Janini, Paszkiewicz, and Vendemia, 2006 and Bee, Meyer, and Sullivan, 2013).[15]

Expenditure in the CEX is inclusive of sales and excise taxes. We therefore impute state-level pre-tax consumption expenditure by dividing by state-specific gross tax rates as described next.

Sales tax rates on goods The Tax Foundation publishes, for every year, standard state sales tax rates and average within-state local sales tax rates.[16] We apply these rates to most categories of goods, except for food consumed at home, drugs, and goods subject to excise taxes. Prescrip-

[14]In the CEX, the lowest income bin is defined as income ”less than $X,” where X varies by year.
[15]Appendix E details the adjustment factors for each good and service.
[16]See, for example, Padgitt (2009).

tion 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, and we use the food-at-home tax rates reported in the Book of States (BOS).[17] 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 service tax rates on a 2007 survey by the Federation of Tax Administrators, which reports state-specific tax rates for 168 services, which we match to the corresponding spending categories in the CEX.[18] For the other years in our sample, we assume that service tax rates are fixed proportions of the standard state sales tax rate.

Tax rates on excise-taxable goods and services We measure excise taxes for the following six spending categories: tobacco, alcohol, motor fuels, public utilities, amusements, and insurance. We label these "excise-taxable goods and services."

Motor fuels, alcohol and tobacco are subject to federal excise taxes. We estimate tax rates by dividing federal tax revenue by aggregate pre-tax expenditure on those goods.

We obtain data on state and local selective sales and gross receipts tax collections from the CSLG and the BOS. We use them to construct excise tax rates by dividing tax revenue by aggregate imputed pre-tax consumption expenditures. Our interpretation is that the tax revenue data include both excise taxes and sales taxes applied to excise-taxable goods and services. Thus, we henceforth use the term "excise taxes" as shorthand for all taxes tied to consumption of excise-taxable goods and services. For tobacco, alcohol, motor fuels, and public utilities we obtain category-specific tax revenue data from the CSLG. For amusements and insurance we obtain state level tax revenue from the BOS.

As the CSLG reports state tax revenue from both households and businesses, we have to take a stance on their distribution. For tobacco, alcohol, amusements, and insurance, we assume that households pay all tax revenue. Following the tax incidence study of the Minnesota Department of Revenue, Tax Research Division (2024), we assume that two-thirds of taxes on motor fuels are paid by households and one-third by businesses.[19]. We assume the same split for taxes

[17] Published by the Council of State Governments for various years. See, for example, Council of State Governments (2016).

[18] Available here: https://taxadmin.org/sales-taxation-of-services/.

[19] This study is considered the "most comprehensive, sophisticated analysis available from any state of the economic incidence of its entire state and local tax system" (Mazerov, 2002, page 15).

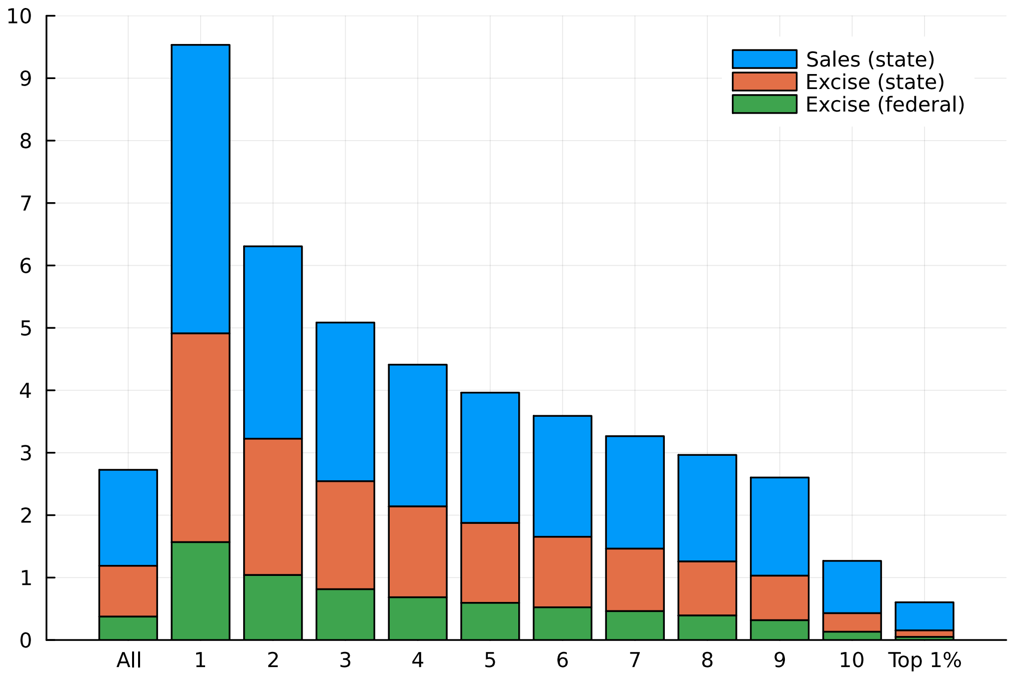

Figure 2: Average consumption taxes expressed as a share of pre-tax income for 2015/2016. See notes to Figure 1.

on public utilities.

Sales and excise 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. 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: low income households face much higher effective rates than richer ones.

There are two reasons why sales and excise taxes are regressive. First, consumer spending rises less than proportionately with income. Second, households with lower incomes consume consumption bundles that are different from, and more heavily taxed than, the ones richer households consume. Figure 3 illustrates both of these sources of regressivity. It shows total household consumption spending as a share of pre-government income and the effective consumption tax rate for different pre-government groups. The consumption tax rate in this figure is computed as consumption taxes divided by pre-tax consumption expenditure.

Spending shares 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 fewer goods, relative to services, and services are generally more lightly taxed. In addition, utilities, fuel,

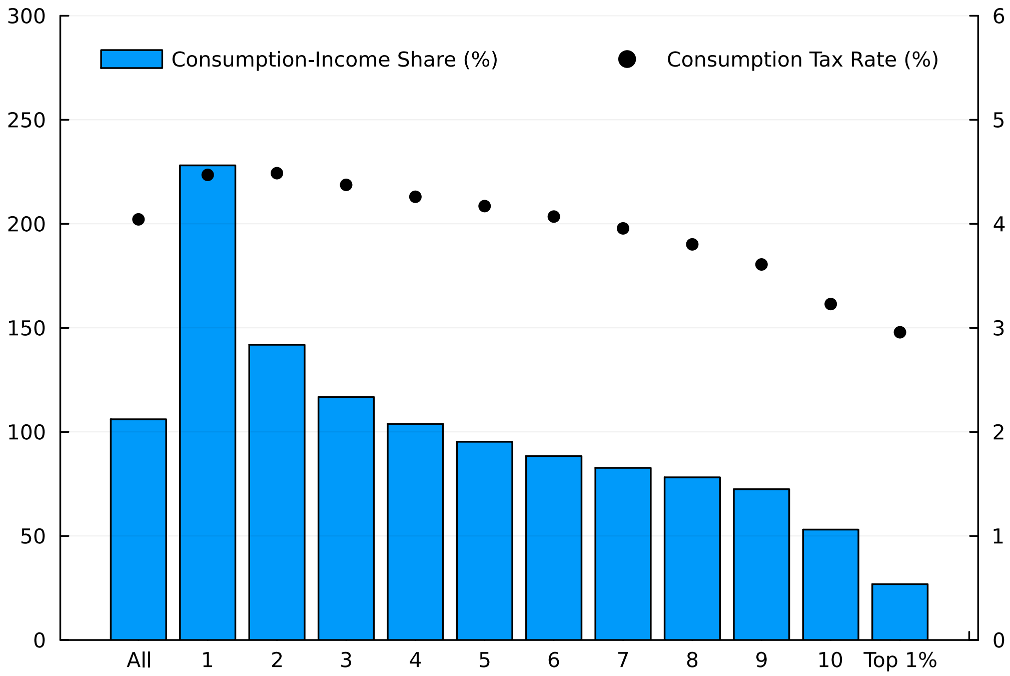

Figure 3: Average household consumption-income shares and consumption tax rates by income for 2015/2016. Consumption-income shares (bars, left axis) are pre-tax consumption spending divided by pre-government income. Consumption tax rates (dots, right axis) are consumption taxes paid divided by pre-tax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

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 sample households. 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), which implies 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 NIPA estimates, but we have not similarly rescaled household income; all tax rates we present are relative to pre-government income as reported in the ASEC dataset (and the SOI). Hence, as discussed in Section 2, income is likely under-reported.[20]

2.3 Property Taxes

Property taxes are typically collected by local governments from homeowners and landlords. Renters are not directly liable for property taxes, but we will assume that landlords pass on, in

[20] The aggregate income components in the ASEC dataset can be calculated from Table C2 in Appendix C.3.

the form of higher rents, a portion of the property taxes levied on rental property. Appendix F provides additional details on all aspects of our property tax imputations.

Homeowners For households with income above the threshold for SOI replacement, we estimate property taxes using the "real estate taxes" variable from the IRS-SOI state-level tables. For other households (the vast majority), we impute property taxes to homeowners using a matching procedure that maps households in our ASEC sample to observationally similar households in the American Community Survey (ACS), which contains self-reported data on house values, rents, and property taxes.[21] 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 education, and the number of housing units in the structure they live in.

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.

Renters There is ample evidence that a significant fraction of property taxes nominally paid by landlords are passed through to tenants (see, for instance, Tsoodle and Turner 2008 and Baker 2024). We can identify renters in the ASEC data, 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 (where rent paid is recorded), following a 'k nearest-neighbors' matching procedure similar to the one described above for owners. This step gives us county- and year-specific estimates for rents paid at the household level. Second,

[21] In contrast, the ASEC data has only imputed property taxes for home owners. Moreover, the CB's 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.

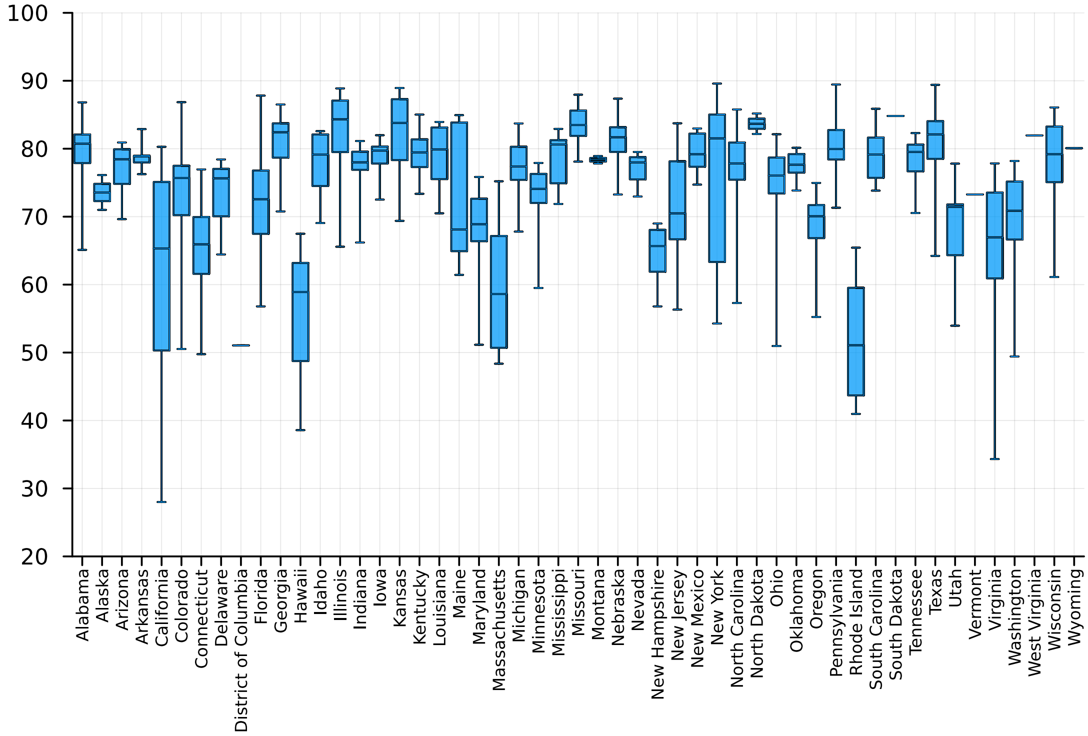

Figure 4: Property tax pass-through by county for 2015/2016, in percent. For each state, the outer ticks show the within-state range of estimated pass-through coefficients across counties. The shaded area plots the inter-quartile range across counties, while the line in the middle represents the median county. The pass-through can be estimated at the state level only for a few small states (South Dakota, Vermont, West Virginia, Wyoming) because county identifiers are suppressed in the ACS for at least one of the variables that enter our pass-through formula.

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 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 passed on to the tenant and consider this amount as the property tax paid by the renter.

Our pass-through model is described in detail in Appendix F.3. The model relies on the idea that in regions where home value primarily reflects inelastically supplied land, property taxes will be borne 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

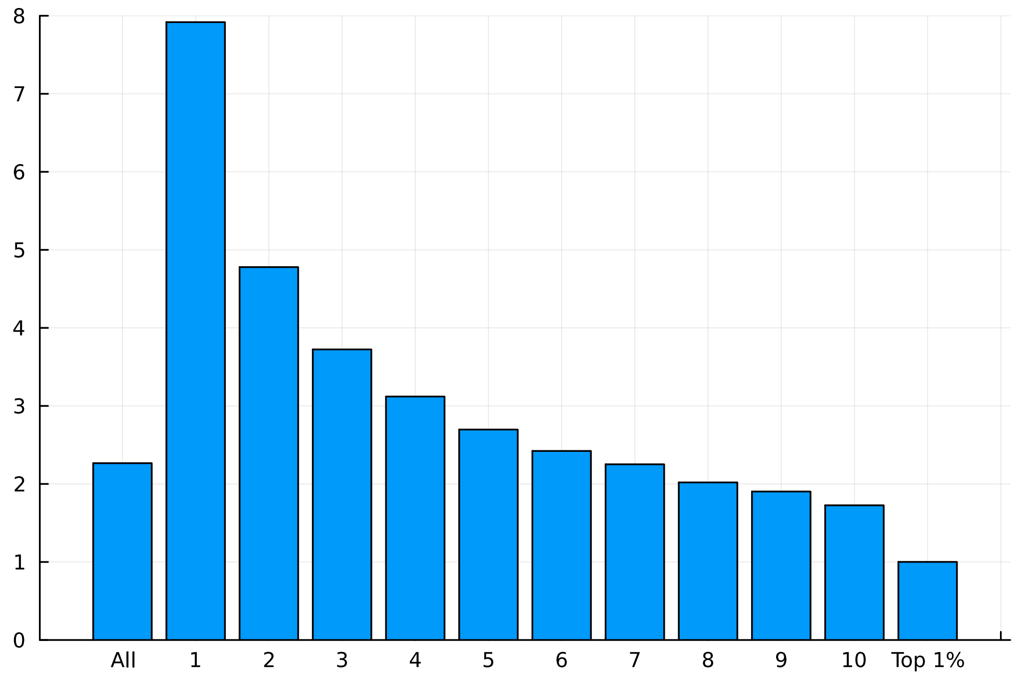

Figure 5: Averages Property tax rates for 2015/2016. Includes homeowners and renters. See notes to Figure 1.

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 the land share of home values 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 the land share of home values 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. 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.

To illustrate the property taxes imputed into our sample in this way, Figure 5 plots property taxes for owners and renters as a fraction of pre-government income for households in different deciles of the income distribution. It is clear that property taxes are regressive. Effective tax rates decline strongly with income; while property taxes claim at least two percent of income for the poorest 80 percent of households, they account for only one percent of income for the richest one percent. Moreover, property taxes are regressive even though imperfect pass-through means that renters – who are more likely to have low incomes – tend to pay lower

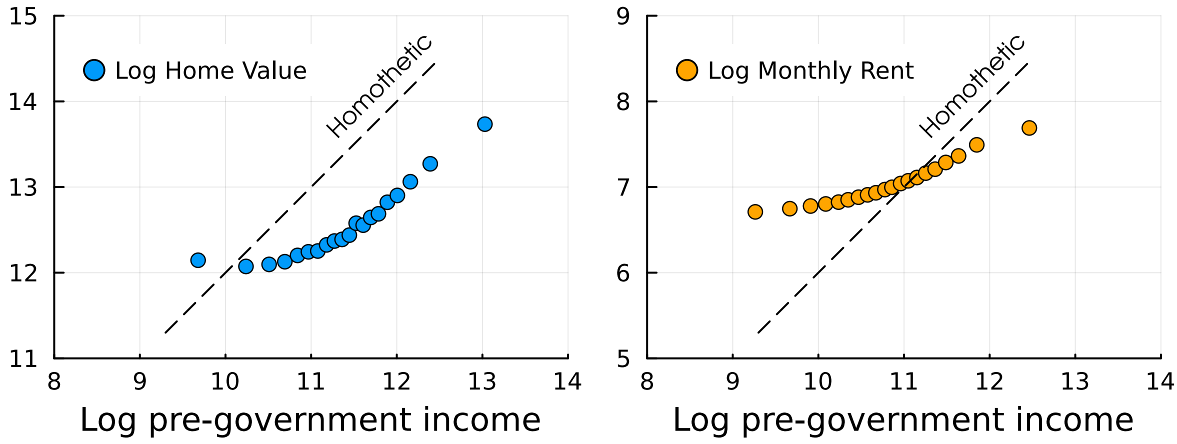

Figure 6: Home values (for owners) and rents (for renters) by pre-government income. Each dot represents the average within one vingtile of households, where households are ranked according to pre-government income. Data source: ACS (2015/2016).

property taxes than homeowners (as shown in Table 3).[22]

To understand the source of property tax regressivity, consider Figure 6. It plots the relationship between mean home values and rents for different pre-government income vingtiles as reported in the ACS. If housing consumption were proportional to income, home values and rents should grow linearly in income with a slope equal to unity, reflecting homothetic spending behavior. The figure indicates a different empirical relationship. Home values increase less than proportionally with 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 incomes.

2.4 Comparing Imputed Taxes to External Estimates

One key test of our imputation models for income, sales, excise and property taxes is to compare our estimates for taxes paid, aggregated across households in the full ASEC dataset (after merging with the IRS-SOI state-level tables), to external estimates of the revenue collected from those taxes. The CSLG 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 CSLG data on state and local income tax revenue very closely. Our model for property taxes also performs well. Our model for con-

[22] Table C1 in the appendix reports the share of homeowners by income group.

sumption tax revenue aligns well for most states, but tends to impute less tax revenue than the CSLG. This discrepancy may reflect a limitation in the external estimates we use for how much businesses pay in general sales taxes. [23]

2.5 Transfers

Table 2 summarizes the transfers we include, whether we categorize them as federal or 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 estimates.

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 Appendix H.1 for details
Supplemental Security Income	x		ASEC (CBO imputed)
Housing Assistance	x		ASEC (CBO imputed); see Appendix H.3 for details
Medicare	x		Imputed as described in Appendix 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 Appendix H.4
Temporary Assistance for Needy Families	x	x	ASEC (INCWELFR); split as described in Appendix H.2
Medicaid	x	x	Imputed and split as described in Appendix H.5

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

Federal transfers Social Security, which is self-reported in ASEC, is an entitlement program in the sense that participation usually requires past contributions. We nevertheless treat it as direct transfers. This is the largest federal transfer program. However, 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.[24] 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

[23] Another potential bias is that we assume all spending in a given state is by state residents. Thus, we miss sales and excise taxes paid by non-residents (such as tourists). Indeed, Hawaii and Nevada are two of states for which our model under-predicts taxes by large amounts.

[24] 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. Heathcote, Storesletten, and Violante (2017) took a different approach, imputing to each household an estimate of the annualized discounted present value of future expected Social Security benefits.

Old-Age component of Social Security. If a Social Security recipient is below age 62, we assume their eligibility is through the Survivor or Disability Insurance components of the program. Otherwise, we assume eligibility is attributable to Old Age.

The ASEC data include a self-reported person-level indicator for Medicare receipt. We follow Habib (2018) from the Congressional Budget Office (CBO) and impute benefit amounts using administrative data on Medicare-financed health expenditures per enrollee. To capture geographic benefit variation, we use state-level (as opposed to national) data, which we obtain from the Centers for Medicare and Medicaid Services (CMS). They also report Medicare spending per enrollee for different age groups at the national level, and we assume the national age distribution applies in all states. However, the dollar value to recipients of Medicare spending may be lower than the amount spent (this issue pertains to all in-kind transfers). We adopt a conservative assumption for that value, assuming it equals the amount by which Medicare eligibility reduces out of pocket health expenditure and spending on private insurance, which is 82 percent of Medicare expenditure according to Finkelstein and McKnight (2008).

We use variables produced by the CBO imputation model for other federal transfers that are known to be under-reported in the ASEC survey.[25] These are the Supplemental Nutrition Assistance Program (SNAP), which provides food stamps, Supplemental Security Income (SSI), and federal housing assistance.[26] 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. The CBO model also imputes Medicaid transfers, which we discuss below.

State transfers There are three transfer programs that we classify as operating at the state level: Unemployment Insurance, Workers' 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 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

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

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

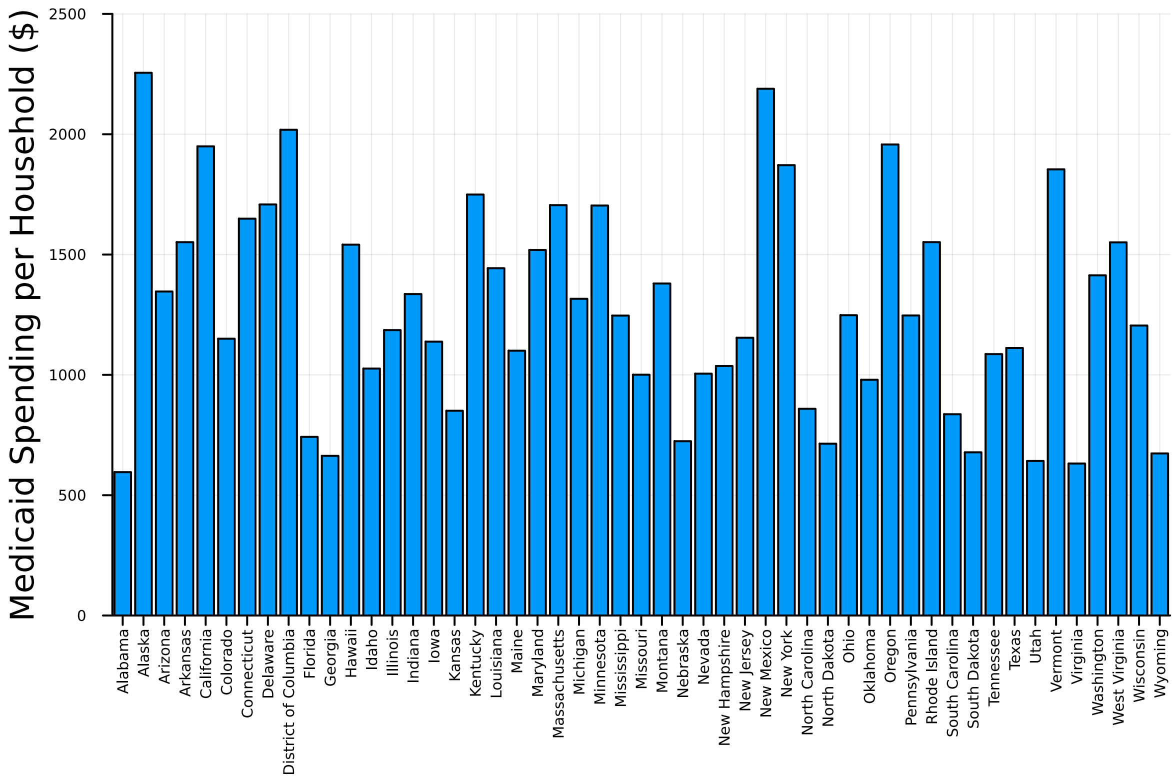

Figure 7: Cash values of state and federal average Medicaid spending per household in our baseline sample (2015/2016). Cross-state variation reflects a mix of variation in enrollment rates plus variation in spending per enrollee. See Appendix H.5 for details.

federal versus state spending shares. For TANF we rely on the self-reported value of transfers in ASEC.[27]

Medicaid is the largest of all U.S. means-tested transfer programs but recipiency 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, it is not designed to match these targets at the state level. We therefore adapt and extend this model to replicate enrollment and spending targets state-by-state. Moreover, 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 corresponds to the average increase in medical spending plus the average decrease in out-of-pocket spending due to Medicaid coverage.[28] Figure 7

[27]The federal TANF funding each state receives is based on the level of state spending on the earlier Aid to Families with Dependent Children (AFDC) program (prior to 1996). See Appendix H.2 for details.

[28]Note that the details of a "no-Medicaid" counterfactual are highly relevant for this calculation. If, in the absence of Medicaid, individuals who are currently eligible for Medicaid would receive more uncompensated care, then part of the value of Medicaid accrues not to recipients but to whoever would otherwise be covering those

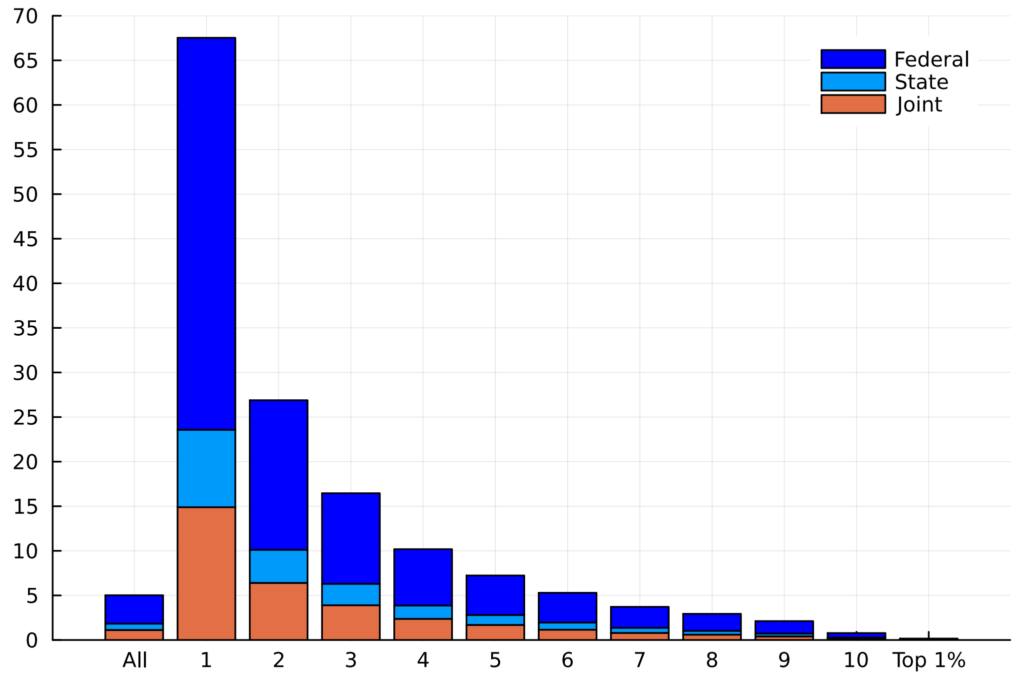

Figure 8: Average transfer rates 2015/2016. See notes to Figure 1.

illustrates the resulting cross-state variation in Medicaid spending per household.

Finally, since state-level spending on Medicaid is matched by federal dollars, we use state-specific Federal Medical Assistance Percentage (FMAP) rates to apportion our Medicaid transfer values into federal versus state components.[29]

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, while they are negligible for households at the top.

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, divided by pre-government income. For our sample, the average net tax rate is about 30 percent, but it differs widely between low and high incomes. For households with the lowest incomes, it is negative at about 50 percent, reflecting that these households receive more transfers than they pay in taxes. From the third income decile, the net tax rate is positive, monotonically increasing, and reaches a maximum of just below 40 percent for the households with the highest incomes.

uncompensated care costs.

[29]FMAP rates are based on state-level relative to national per capita income. See Appendix H.5 for more details.

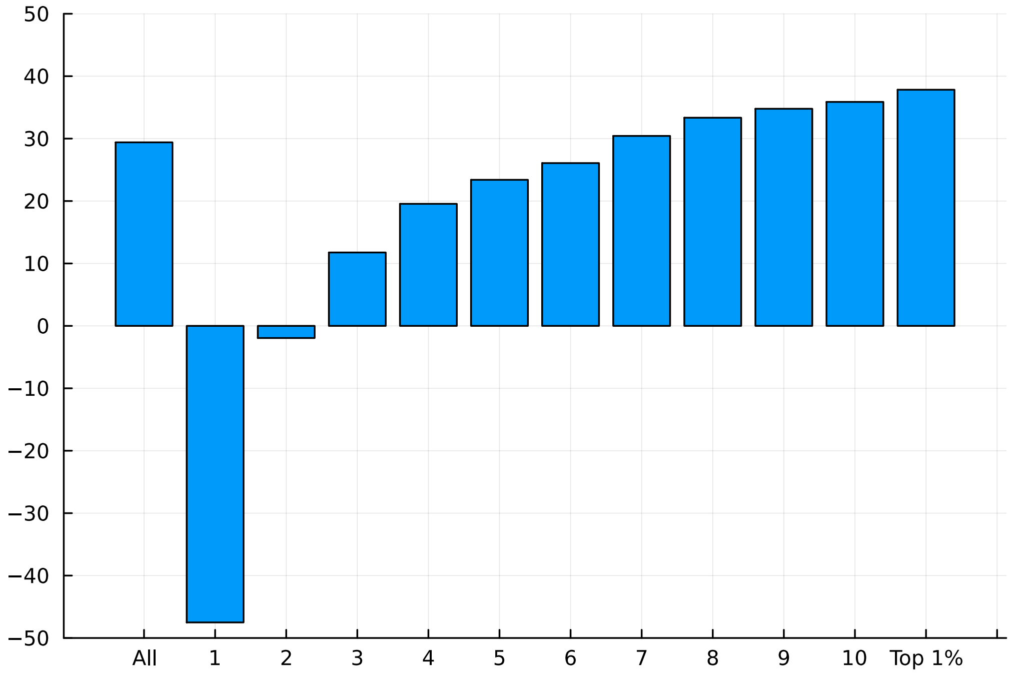

Figure 9: Average total tax (total taxes net of transfers) rates. 2015/2016. See notes to Figure 1.

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 C1 in Appendix C.2 is a more comprehensive version of this table. Table C2 in Appendix C.3 reports the corresponding statistics for the full ASEC dataset—that is, before dropping households that do not satisfy our age- and income-based sample selection criteria.

3 Aggregate 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 different ways to overall progressivity or regressivity. To summarize the overall progressivity in a simple index, we now approximate the tax and transfer system using the parametric functional form used by Benabou (2002), Heathcote, Storesletten, and Violante (2017), and 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, income after taxes and transfers, $y - T(y)$, is related to pre-government income y according to

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

	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). Numbers have been computed using ASEC household weights. Column "All" reports average income and tax and transfer values for the entire sample. Columns 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 "Top 1%" refers to the one percent of households with the highest incomes. All values 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.

where the coefficient $\tau \leq 1$ indexes progressivity.[30]

For convenience, in what follows we refer to (2) as the HSV tax function.

As in Heathcote, Storesletten, and Violante (2017), we estimate τ by running ordinary least squares regressions on our cross-sectional ASEC sample given household level values for y_i and T_i.[31] We consider a range of different measures of T_i, corresponding to different subsets of taxes and transfers.

First, we include only federal taxes and transfers in T_i and estimate a coefficient for federal progressivity, τ_f. Next, we use only state and local taxes and transfers to estimate aggregate state progressivity, τ_s. Finally we include all taxes and transfers to estimate overall progressivity τ.

Specification	**Level**	**τ estimate**	**T_i measure**
Baseline	Federal	0.104	Income Taxes
		0.198	- Transfers
		0.195	+ Excise Taxes
	State	0.013	Income Taxes
		0.038	- Transfers
		0.019	+ Property Taxes
		0.006	+ Sales Taxes
		-0.004	+ Excise Taxes
	Federal & State	0.202	Income Taxes, Transfers, Property Taxes, Sales Taxes, Excise Taxes
Extension 1	Federal	0.214	+ Corporate Income Taxes
	State	-0.011	+ Corporate Income Taxes + Business Taxes
	Federal & State	0.227	+ Corporate Income Taxes + Business Taxes
Extension 2	Federal	0.280	- Extra Medicaid and Medicare - Spending on Goods and Services
	State	0.124	- Extra Medicaid - Spending on Goods and Services
	Federal & State	0.372	- Extra Medicaid and Medicare - Spending on Goods and Services

Table 4: Estimates for aggregate progressivity from the pooled national sample. See Table 2 for the programs included in federal and state transfers. All estimations use ASEC household weights. As the estimates are based on a non-linear function, "Federal" and "State" do not add up to "Federal & State."

Table 4 reports our estimates for aggregate federal and state tax and transfer progressivity. In the top part of the "Baseline" panel, we start with federal taxes and transfers. The federal tax and transfer system is quite progressive. For federal income taxes, we estimate $\tau = 0.104$.

[30]It is useful to note that $\tau = 0$ denotes a proportional system and $\tau > 1$ (< 1) a progressive (regressive) system. In addition, $1 - \tau$ equals the ratio of the standard deviation of log disposable income to the standard deviation of log pre-government income. In the next section, we show next how values of τ and λ map into marginal tax rates.

[31]Note that pre- and post-government income appear in logs in our estimation equation. Thus, we must drop households for whom either income is non-positive. Fortunately, this is a negligible fraction of households in our baseline sample: we drop at most 0.07 percent of households.

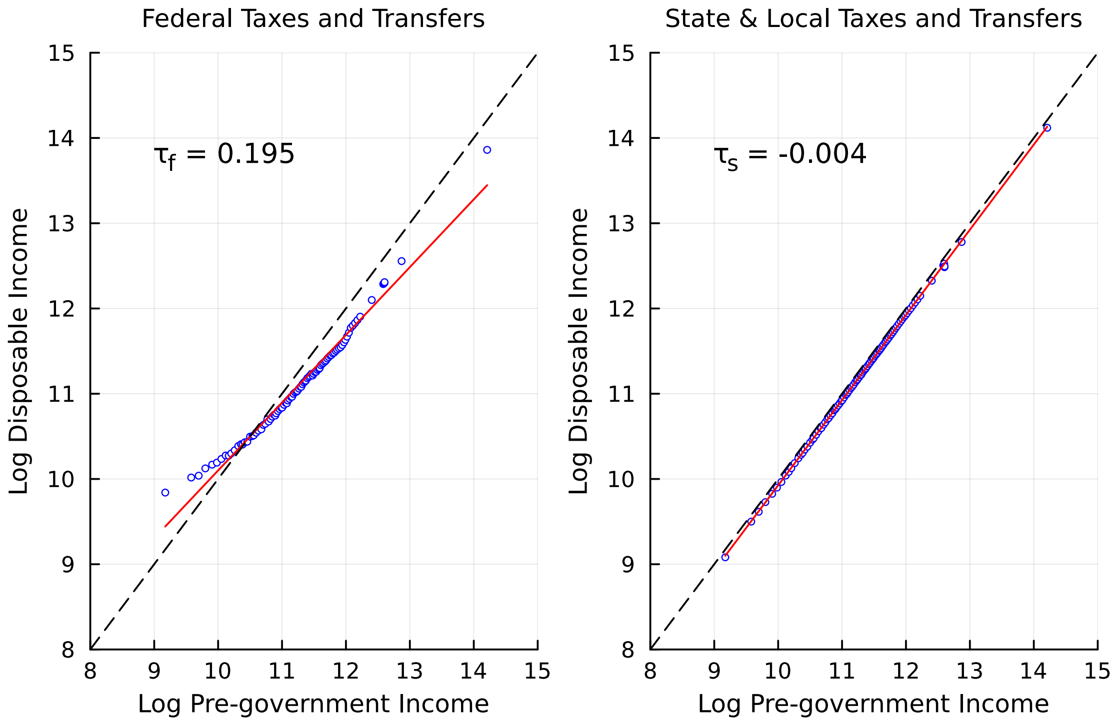

Figure 10: Fit of the HSV tax and transfer function. Left panel: T_i includes federal taxes and transfers. Right panel: T_i includes state and local taxes and transfers. Each dot corresponds to one percent of the 2015/2016 sample, ranked by pre-government income. Estimation uses ASEC household weights.

Adding federal transfers raises τ to 0.198 and including federal excise taxes gives an estimate of 0.195.

The next rows in the baseline panel isolate the progressivity embedded in state taxes and transfers. 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; 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 -0.004.

In the last line of the "Baseline" panel we include all federal and state and local taxes and transfers to compute disposable income. The resulting estimate is 0.202, which represents the overall progressivity provided by the entire U.S. tax and transfer system.[32]

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).

The log-linear tax and transfer function fits well at most income levels but implies net taxes that

[32]The baseline estimate in Heathcote, Storesletten, and Violante (2017) was slightly lower at $\tau = 0.181$. However, their analysis included a smaller set of taxes and transfers.

are too high at very low (bottom 5 percentiles) and very high (top 5 percentiles) income levels. Ferriere, Grübener, Navarro, and Vardishvili (2023) and Boar and Midrigan (2022) add a lump-sum transfer to our benchmark log-linear tax and transfer function. Naturally, introducing this extra parameter allows for a better fit to the data. Nonetheless, we will retain the simple HSV function as our baseline, because it is tractable and widely used, and because it allows us to compare the extent of redistribution across different states using τ as a univariate index of progressivity. In Appendix O we discuss further the more general HSV-plus-lump-sum-transfer specification and report state-by-state estimates for that functional form. We also discuss the implications of estimating the τ parameter in the HSV function following a Poisson Pseudo Maximum Likelihood (PPML) approach as an alternative to our baseline log OLS estimation procedure, as advocated by König (2023).

For state taxes and transfers, we have also computed the Suits (1977) index, which is a non-parametric measure of progressivity. Figure 11 ranks households by pre-government income and plots the cumulative share of different sorts of taxes paid and transfers received against cumulative total pre-government income. Different state taxes and transfers are added cumulatively following the sequence in Table 4. The Suits index for a given measure of taxes is the area under the 45 degree line minus the area under the Lorenz curve for that tax measure, divided by the area under the 45 degree line. Thus, proportional tax systems have an index value of zero, and tax systems are progressive (regressive) according to this measure if they are associated with positive (negative) index values.

The Suits index offers a characterization of different state taxes and transfers similar to our τ measure. To see this, note that the Lorenz curve for state income taxes lies below the 45 degree line, implying a positive Suits index value (i.e., progressivity) for those taxes. Subtracting transfers makes state tax systems appear even more progressive.[33] Adding property taxes dramatically moves up the Lorenz curve and reduces the Suits index value. This result indicates that these taxes reduce overall progressivity. Adding sales and excise taxes reduces the index value further, so that on net, the sum of all state and local taxes and transfers amounts to a near proportional system. This finding is consistent with our estimate of state-level progressivity based on the log-linear function (see Table 4).

Finally, to illustrate the implications of the τ estimates presented in Table 4 (and the corresponding λ estimates), Figure 12 translates them into profiles for marginal and average tax rate

[33]When including transfers, the lowest-income households, up to a cumulative share of total pre-government income just above 20 percent, account for a negative cumulative share of the total net tax burden. In other words, their transfers received exceed their taxes paid.

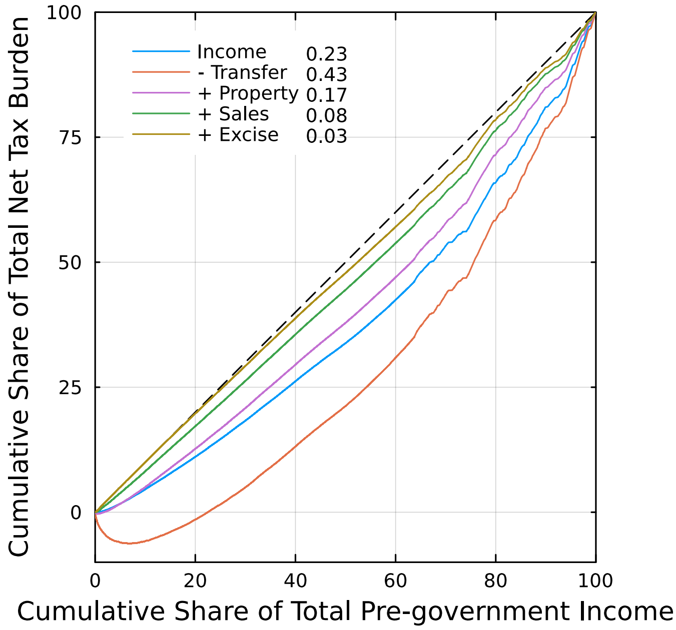

Figure 11: Lorenz Curves for the aggregate state taxes and transfers in Table 4. Suits (1977) index value shown next to each tax. Computed for 2015/2016 using ASEC household weights.

schedules. 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, which reflects that they are regressive taxes.

4 Cross-State Variation in Net Tax Rates and Progressivity

We now explore differences in net tax and transfer rates, and in overall tax and transfer progressivity, across all U.S. states and the District of Columbia.

4.1 Reweighting State Income Distributions

U.S. states differ in both their tax and transfer systems and their pre-government income distributions. If the tax and transfer system in each state were perfectly represented by equation (2), these differences would not impact state-specific estimates for progressivity τ_s. In practice, however, this simple specification does not perfectly fit the data (see Figure 10), and as a result, one might worry that cross-state variation in the shape of the state income distribution might affect the estimated value of τ_s.

To address this potential concern, we henceforth reweight households state by state, so the

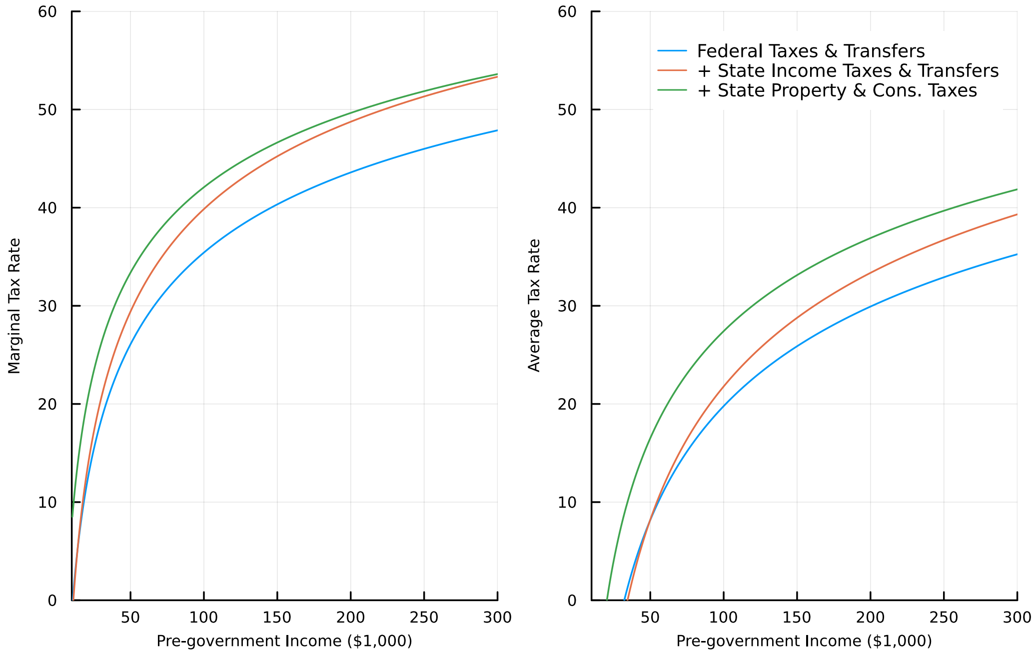

Figure 12: Average economy-wide marginal and average tax rate schedules for household pre-government incomes between $10,000 and $300,00, in percent, for different measures of taxes and transfers (see Table 4). Refers to 2015/2016.

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 ten income bins. Then, for each state, we compute scaling factors for households within each national income bin, so that when we rescale the original ASEC weights by those factors, ten percent of reweighted state households lie within each bin. We refer to these rescaled weights as "adjusted (ASEC) weights." See Appendix I for more details.

4.2 State Level Tax and Transfer 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 turns out to play an important role in our subsequent analysis of cross-state variation in state tax and transfer progressivity.

Figure 13 plots state and local average rates for income taxes, sales and excise taxes, and property taxes. In this and 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 state sales tax.

Figure 14 stacks these components 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

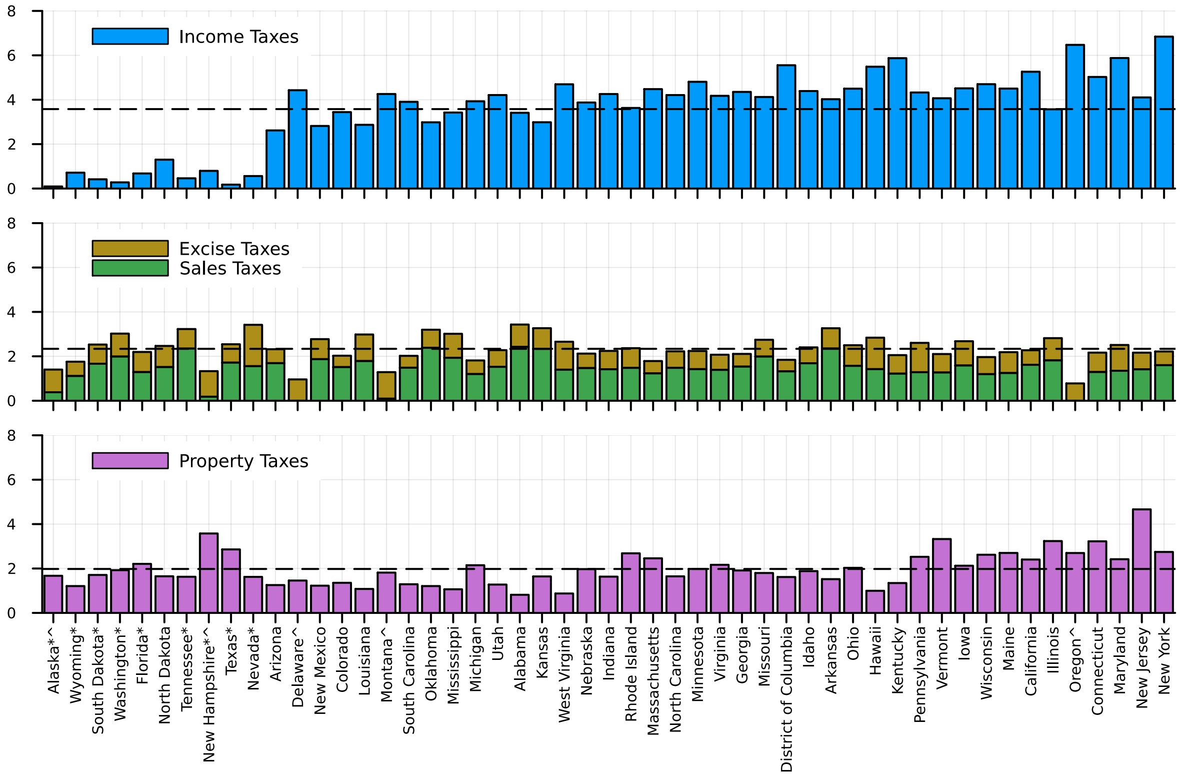

Figure 13: Average tax rates by state in our ASEC sample, 2015/2016. The horizontal dashed lines indicate national averages. A $*$ superscript denotes states that have no state income tax, and a $\wedge$ superscript denotes states that have no state sales tax. Computed after re-weighting households as described in Section 4.1.

income – is the sum of all these components. In both Figures 13 and 14 states are ordered left to right from the one with the lowest net tax rate (Alaska) to the one with the highest (New York).

The first clear message is that net tax rates vary substantially across states. Net taxes range from minus three percent of household income in Alaska to plus eleven percent 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.[34] They constitute nine out of the ten states with the lowest overall net tax rates. Figure 13 illustrates that these states 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 sales taxes all collect quite similar shares of income via consumption

[34]State income tax revenue is not exactly zero in these states, because the IRS-SOI state-level tables indicate a small, positive amount of state income taxes paid by high-income residents of these states. This reflects that residents in states without state income taxes can also earn income in other states where it is taxable. New Hampshire does not tax labor earnings, but it does tax interest and dividend income.

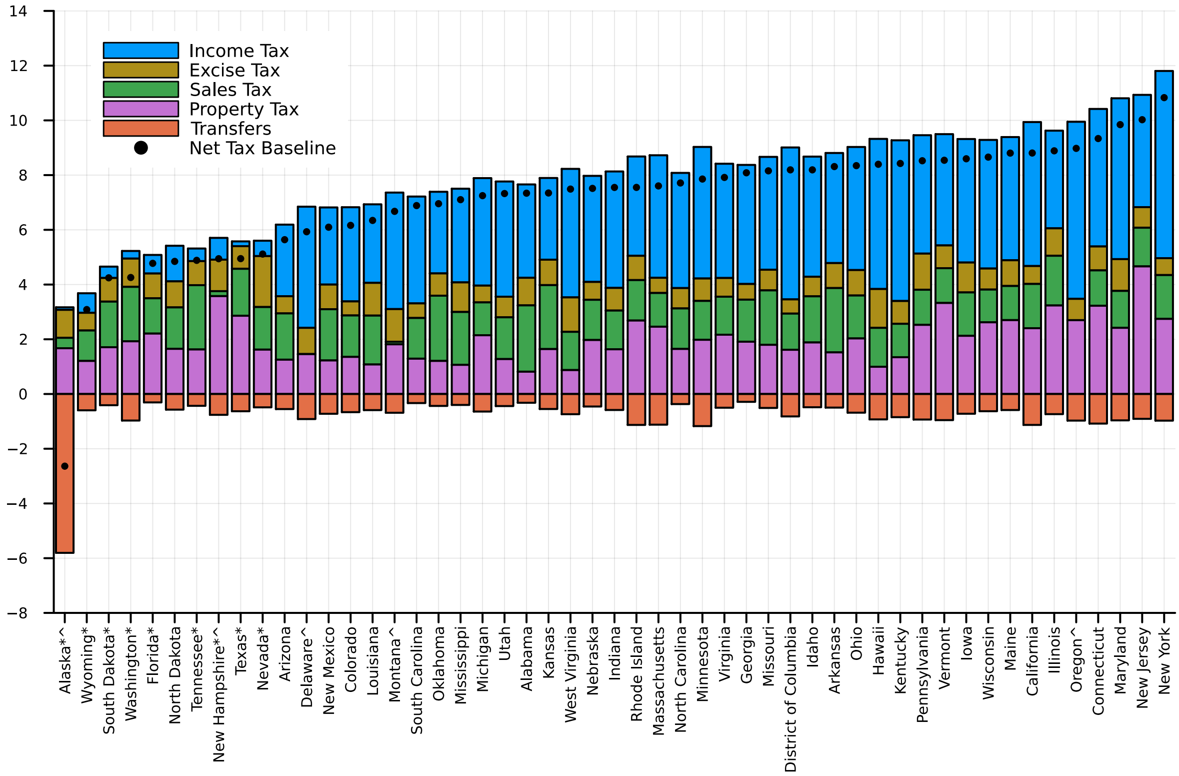

Figure 14: Average tax and transfer rates by state, in percentages, in our ASEC sample, 2015/2016. A $*$ superscript denotes states without state income tax, and a $\wedge$ superscript denotes states without state sales tax. Transfers are the state transfers described in Table 2. Computed after re-weighting households as described in Section 4.1.

taxes. The outliers are the states without state-wide sales taxes (New Hampshire, Oregon, Montana, Alaska and Delaware).

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 exhibit some variation across states, but they account for a relatively small share of income in all states except for Alaska, where the Alaska Permanent Fund Dividend is large and drives the net tax rate negative.[35] With the exception of Alaska, low-tax states also tend to have relatively low transfers, whereas state transfers tend to be somewhat larger in the states with the highest state tax burdens.

[35] In addition, the dividends of the Alaska Permanent Fund are distributed lump-sum, whereas transfers in other states target low-income households.

4.2.1 California versus Texas

Before turning to state level estimates of the progressivity parameter τ_s, we contrast the two largest U.S. states, California and Texas, which have quite different tax and transfer systems.

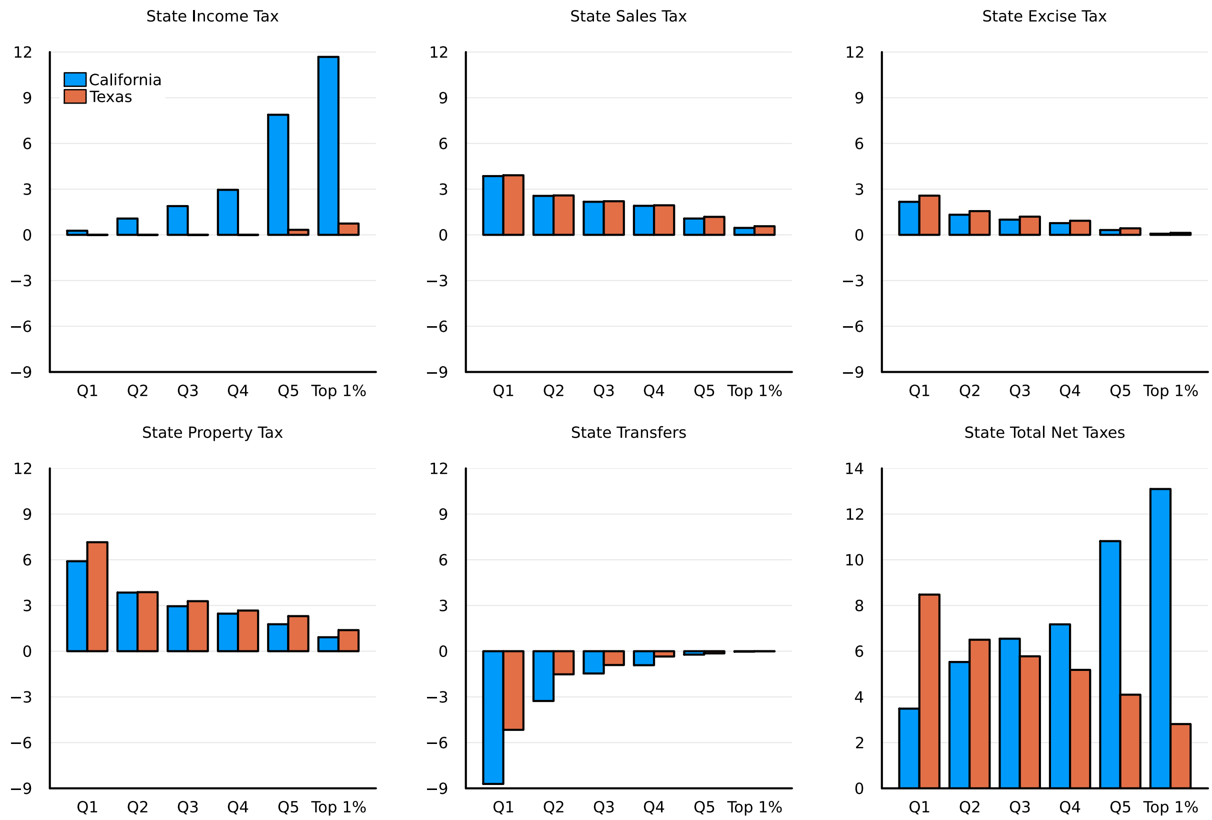

Figure 15: Average tax and transfer rates for California and Texas in our ASEC sample, 2015/2016. The plot shows state and local taxes paid and transfers received across five quintiles of the state pre-government household income distribution and for the top one percent (after re-weighting as described in Section 4.1).

Figure 15 plots taxes paid, as a share of pre-government income, for each quintile of the (reweighted) state pre-government income distribution, as well as for the top one percent, averaged across 2015 and 2016. The top left panel indicates that California has a strongly progressive state income tax, whereas Texas has no state income tax. The top middle and top right panels show that sales and excise taxes are similar in the two states across all income bins.[36] Conversely, property taxes (bottom left) are slightly higher in Texas.[37]

Transfers (bottom middle) are much larger in California than Texas, especially at the bottom of the household income distribution. What accounts for this difference? First, California has

[36] The standard state plus average local sales tax rate in Texas in 2015 was 8.05 percent, compared with 8.44 percent in California.

[37] 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 percent in 2015 and 2016, while Texas had no corporate income taxes.

a larger fraction of residents collecting unemployment insurance benefits, and UI benefits are also higher per recipient. Second, California has a much larger fraction of residents receiving Medicaid benefits.

The bottom right panel of Figure 15 plots total state taxes net of transfers. The plot illustrates that California and Texas have quite different tax systems. The California system is relatively progressive: net tax rates rise strongly with income. The Texas system, conversely, is relatively regressive: the poorest households face the highest net tax burden. The reason California is so much more progressive is clear; it has progressive income taxes and more progressive transfers.

Figure 16 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* income tax rates are identical only up to the fourth quintile. They are lower in California for higher incomes because of the State and Local Tax (SALT) deduction; until tax year 2018, itemizing taxpayers could deduct all state and local taxes when computing federal taxable income. Moreover, *federal* transfers at the bottom are larger in California than in Texas. The reason is that California spends more state money on Medicaid and therefore also receives more federal matching dollars.

4.3 State Level Progressivity

Figure 17 plots estimates of the progressivity parameters τ_s for state taxes and state transfers (the black dots). States are ranked from least to most progressive. The figure also shows contributions to overall state progressivity from each component of taxes and transfers (the colored bars). For example, the contribution of sales taxes to progressivity in Texas is estimated by regressing log household pre-government income minus sales taxes for Texas households on a constant and log pre-government household income.[38]

In each state, transfers contribute positively and significantly to progressivity, with sizable variation across states. In particular, transfers deliver much more redistribution in Alaska, Minnesota and the Northeast than in the rest of the country. Transfers contribute especially strongly to progressivity in Alaska thanks to the Alaska Permanent Dividend Fund, which pushes Alaska to the top of our progressivity ranking.

State income taxes contribute positively to progressivity in all states, but the progressivity of

[38]Note that the progressivity contributions of different taxes and transfers do not exactly add up to the overall progressivity estimates, because of the log transformations.

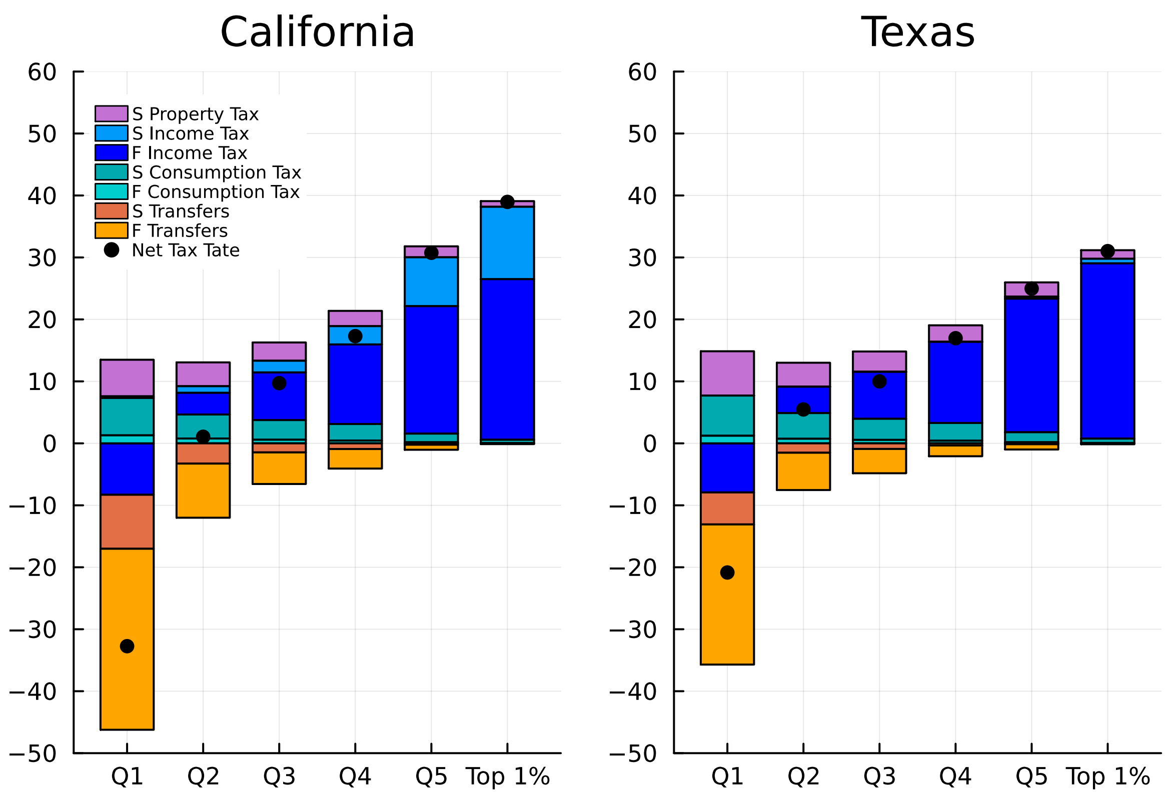

Figure 16: Average state and local as well as federal tax and transfer rates for California and Texas, 2015/2016. The plot shows state and local (S) as well as federal (F) taxes paid and transfers received across five quintiles of the state pre-government household income distribution and for the top one percent (after re-weighting as described in Section 4.1).

those taxes varies across states. All 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. This result reflects the high property tax rates in those states, as shown in Figure 13. This pushes those states down the overall progressivity ranking. Sales taxes are similarly regressive in all states that levy them, and excise taxes are regressive everywhere. Illinois is the most regressive state in our ranking because it levies relatively high sales and property taxes, and because it taxes income at a flat rate.[39]

The rank correlation between our τ_s estimates and the Suits index for state taxes net of transfers is 0.84, indicating that this alternative progressivity measure delivers a very similar ranking.[40]

The Institute of Taxation and Economic Policy (ITEP) also computes a state-level index of progressivity, which it labels the ITEP Tax Inequality Index. Our progressivity ranking for 2015 has

[39]Figure J1 in Appendix J.1 plots contributions to progressivity from each tax separately for each state and compares them with the national averages.

[40]We exclude Alaska when computing the rank correlation as the Suits index is not suited for tax systems which deliver negative net total taxes.

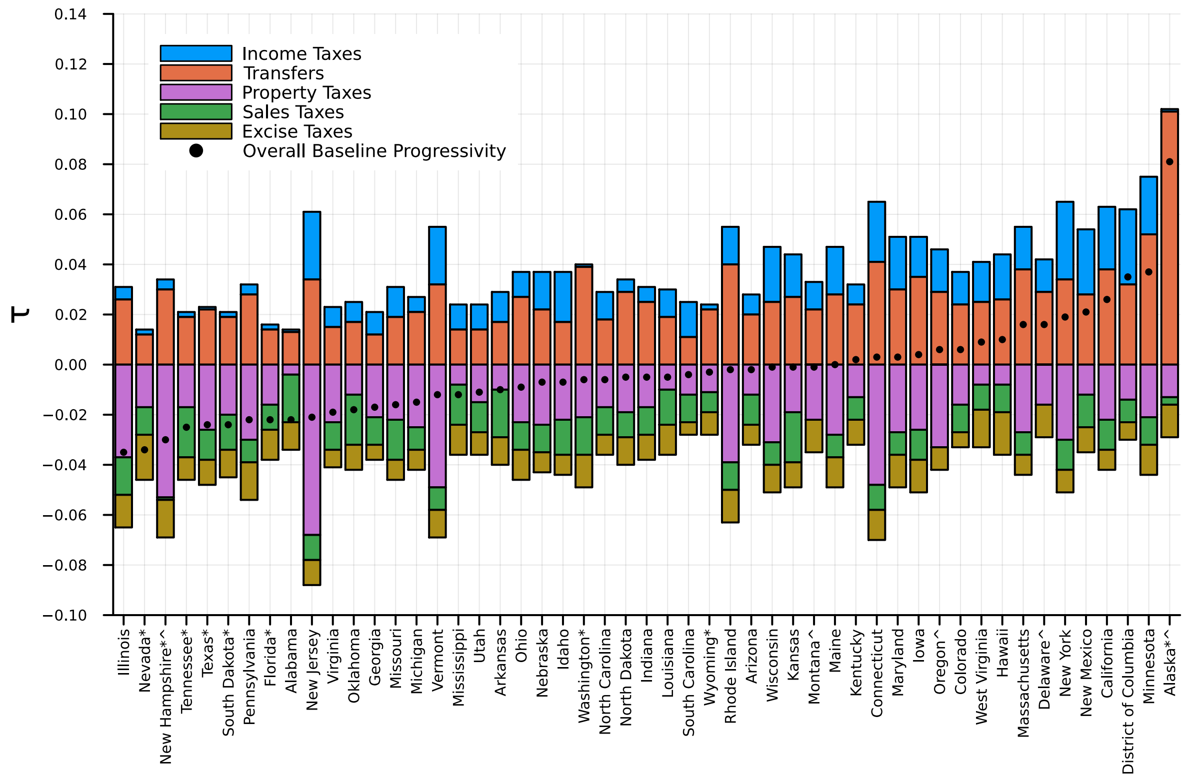

Figure 17: State progressivity decomposition. The plot shows estimates for progressivity induced by each of the state level taxes and transfers indicated in the legend, considering one tax at a time, using household weights constructed as described in Section 4.1. The black dots report overall state baseline progressivity, τ_s. Estimates are for 2015/2016.

a rank correlation of 0.55 with the 2015 Inequality Index. One reason the two rankings differ is that the ITEP considers the impact of taxes only, whereas we include transfers in our analysis. Another is that the formula underlying the ITEP index heavily emphasizes redistribution at the top of the income distribution, while our τ measure incorporates redistribution throughout the income distribution. Indeed, the rank correlation between the state top income tax rate and the ITEP Inequality Index in 2015 is 0.74, while this correlation with our τ measure is 0.47.

In Appendix O we report state-level progressivity estimates, τ_s, using both the log OLS and PPML estimation procedures, as well as estimates for the more flexible specification that adds a lump sum transfer to the log-linear specification in equation (2). The PPML τ_s estimates are lower than our baseline log OLS estimates, but the state progressivity ranking is very similar across both estimation methods.

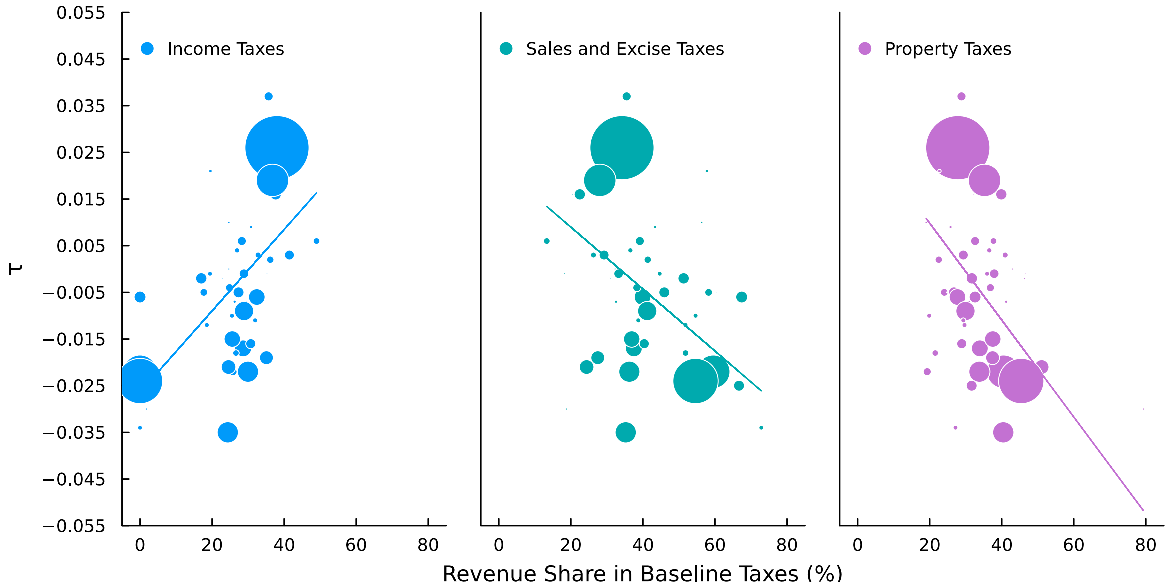

Figure 18: Estimated state tax progressivity τ_s and tax revenue shares. Excludes Alaska. Dot size is proportional to state population. Baseline taxes are income, sales, excise and property taxes. Revenue data are from the CSLG. Refers to 2015/2016. Lines are the least squares best fits when states are weighted by population. The R^2 values are 0.41, 0.19 and 0.18.

4.4 State Progressivity Correlates

Figure 18 illustrates that states that rely more income taxes tend to have more progressive overall tax and transfer systems. The opposite is true for states that rely more on sales, excise and property taxes. This pattern should not come as a surprise given our earlier evidence that income taxes are typically progressive, while sales and property taxes are inherently regressive.

Figure 19 plots average state net tax rates (Figure 14) against our state-level estimates of progressivity (Figure 17). 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, which reflects their heavy reliance on regressive property taxes. One reason why the average state net tax rate and state tax progressivity are generally positively correlated is that states without a state income tax do not make up for that missing revenue stream by setting higher sales or property tax rates. That observation merits further study, but it is plausible that no-income-tax states are concerned that higher sales tax rates would lead to revenue losses due to increasing cross-border shopping.[41] In addition, property taxes are an imperfect substitute for income taxes because property taxes are traditionally dedicated to spending at the local level and cannot easily be used to fund state-level spending on Medicaid or higher education.

Of course, this raises the question of why some states have a state income tax, while others

[41] See recent evidence in Davis, Knoepfle, Sun, and Yannelis (2018) and Baker, Johnson, and Kueng (2021).

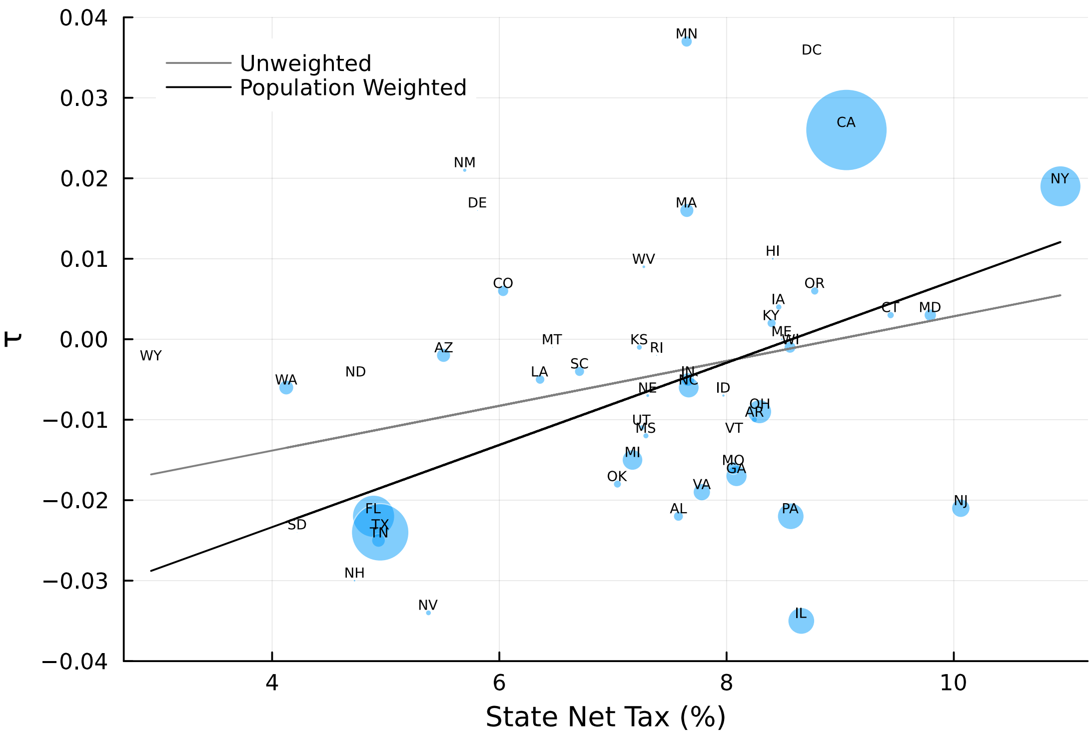

Figure 19: Comparison of state average net tax rates and estimated state tax progressivity τ_s. Excludes Alaska. Dot size is proportional to state population. Estimates for 2015/2016. The gray line is the least squares best fit when states are weighted equally. The black line is the best fit when states are weighted by population. The R^2 values are 0.08 and 0.23.

do not. The historical record shows that the introduction or elimination of a state income tax system is a rare event: New Jersey was the most recent state to introduce a state income tax, in 1976, and Alaska is the only state to have ever repealed a state income tax, in 1979. Thus, states that introduced income taxes long ago tend to have relatively progressive overall tax and transfer systems today.[42]

Figure J2 in Appendix J.1 plots the geography of our τ_s estimates, with more progressive states colored in darker shades. As this figure indicates, states in the South tend to be the least progressive. One driver of this pattern is that southern states tend to have less generous and inclusive social insurance systems, which limits the contribution of transfers to overall progressivity. Moreover, two southern states, Florida and Texas, do not have income taxes.

Finally, we investigate whether our estimates of state tax and transfer progressivity correlate with measures of inter-state migration. All else equal, one would expect relatively high (low) income households to prefer to live in states with relatively regressive (progressive) tax and transfer systems. To explore this issue, we turn to the American Community Survey (ACS),

[42] Howe and Reeb (1997) provide a historical account of the emergence and evolution of state and local taxes. See also OECD (2016), Chapter 2.

which provides information on respondents' states of residence at the time of the survey interview and one year prior to the interview. We start by constructing an ACS sample that satisfies the same age and income restrictions we impose in our ASEC / SOI sample. For all sample households whose heads reported a change of state from the previous year, we compute the implied change in the (reverse) state progressivity ranking. For example, a household moving from Alaska (our most progressive state) to Illinois (our least progressive state) is recorded as $51 - 1 = 50$. The reverse move would be recorded as -50. We then compute mean ranking changes for different pre-government income groups and report them in Figure 20.

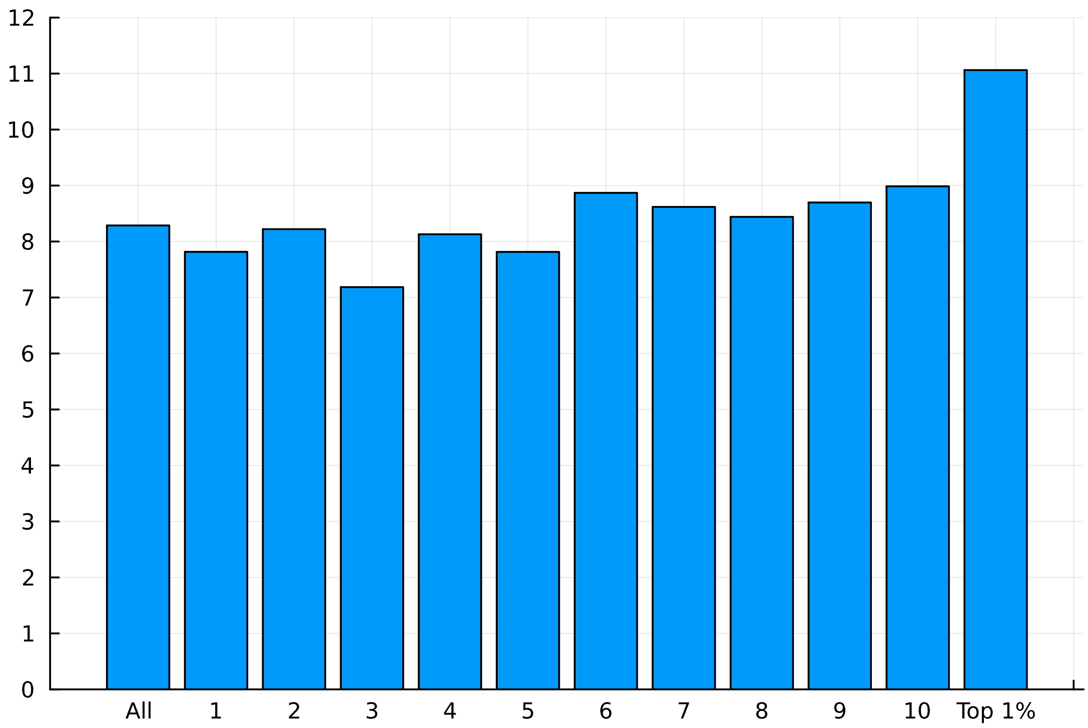

Figure 20: Changes in state progressivity ranking for households that moved states one year prior to 2015 and 2016. Positive numbers indicate moving to a less progressive state. Ranking changes are plotted for all sample households in the ACS, for 10 deciles of the household pre-government income distribution, and for the top 1 percent of households by income. For each bin, average ranking changes are shown. The income thresholds defining the bin boundaries differ from those in earlier plots for two reasons: (1) the source for income here is the ACS instead of ASEC / SOI, and (2) the sample here is restricted to inter-state movers, and the income distribution for this selected group differs from the distribution of the entire sample.

The figure indicates that households at *all* income levels tend to migrate from more progressive to less progressive states. Specifically, averaged across all moving households, the current state of residence was 8.2 spots below the previous one in the progressivity ranking. In part, this finding reflects the fact that states in the South tend to be both among the states with the least progressive tax systems (see Figure J2 in Appendix J.1) and also among the states that have attracted most inter-state migrants during our period of analysis.[43]

While low tax progressivity appears to be a draw for all movers, it appears to be a particularity salient driver of destination choices for higher income movers. The one percent of moving households with the highest incomes are especially drawn to less progressive states. Compared with the average moving household, they move to states that, on average, are three additional rungs down the progressivity ranking. This finding is consequential, as these households account for a large share of taxes paid: the top one percent of households by pre-government income in our baseline sample account for 30 percent of total state and local income taxes paid (see Table 3). Thus, losing high income residents can significantly erode a state's tax base.[44]

4.5 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 these three periods.

Progressivity appears generally higher in 2010/11 than in the other years. One reason for this is that the unemployment rate was notably higher then; in the aftermath of the Great Recession, the national unemployment rate was around 9 percent in 2010/11 but below 5 percent in other sample years. In response to higher unemployment rates (and longer unemployment spells), many 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.[45] This finding is in line with Heathcote, Storesletten, and Violante (2020), who argue that progressivity is generally increasing in recessions and falling in booms.

Between 2010/11 and 2015/16 the share of adult Americans covered by Medicaid increased substantially, thanks to the Affordable Care Act.[46] However, while some states opted to expand Medicaid insurance before 2015/16, others did not. This can account for the increasing τ_s dispersion visible in the green kernel density plotted in Figure 21 relative to the blue and red ones. See Appendix J.2 for more results and details, including a breakdown of the time variation in each state tax and transfer component.

[43] See, for example, Figure 1 in Kerns-D'Amore, McKenzie, and Locklear (2023).

[44] Moretti and Wilson (2017) show that top scientists' migration decisions are sensitive to state tax differentials.

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

[46] The Affordable Care Act (ACA) was signed into law in 2010 but most of its provisions started from 2014. Figure H2 in Appendix H.5 shows more information on how the ACA affected Medicaid enrollment.

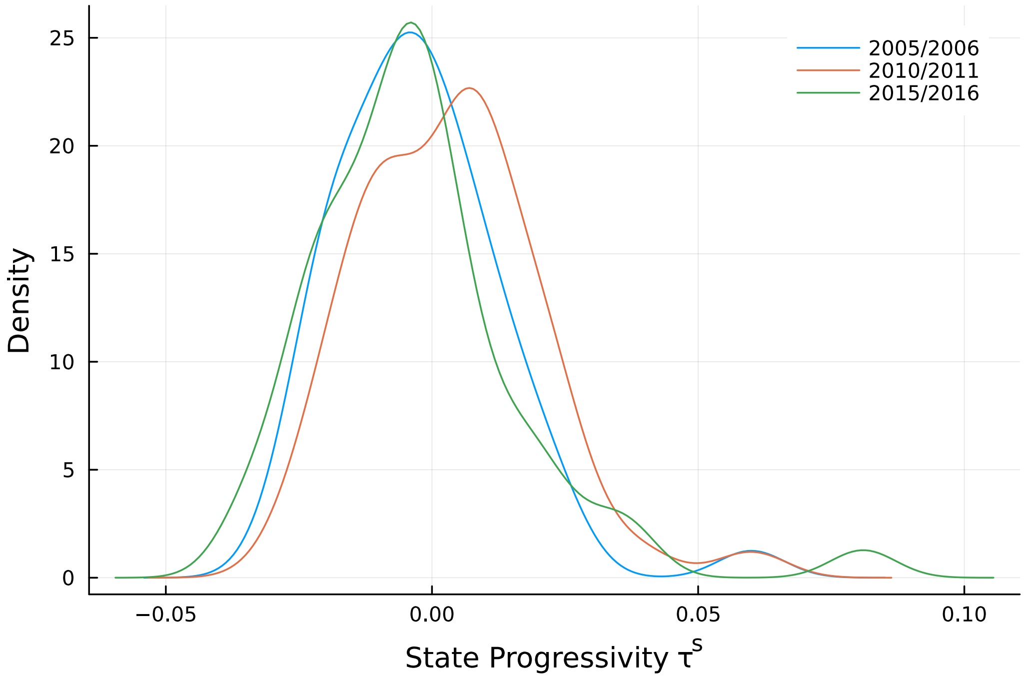

Figure 21: Kernel density estimate of state progressivity, τ_s. Estimates use all state taxes and transfers discussed in Section 4.3.

5 Extensions

5.1 Extension 1: Corporate Income Taxes and Business Taxes

In addition to the taxes we include in our baseline analysis, 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 corporate income tax collections amounted to about 1.5 percent of U.S. GDP in 2016, state collections represented only about 0.2 percent 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 percent of state GDP.

In addition, a considerable portion of total state and local tax collections are raised from businesses—for example, through property taxes on their structures and sales taxes on business inputs. Figure A3 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 percent.

We therefore now extend our analysis of state tax progressivity by including state (and federal) corporate income taxes and state and local taxes collected from businesses. As 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 under-reported in survey data as well as in tax returns, which are the basis for the SOI state-tables we use to augment information on high-income ASEC households. As a result, the base for these taxes is presumably too low in our sample.

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

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; these percentages are based on a summary of the existing literature.[47] On the basis of these same studies, we also take into consideration that the incidence on labor is extremely unequal and posit that half of the labor share (or 20 percent of the total tax) accrues to households in the top 1 percent of the labor earnings distribution, while the other half falls on households between the 99th and 75th percentiles of the distribution.

For *federal* corporate income taxes, we measure total corporate income tax revenue and allocate 60 percent across all households in proportion to dividend income. We then allocate 20 percent to households in the top 1 percent of all 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

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

earnings, as described above.

Figure 22 reports the resulting effective corporate income tax rates across the income distribution. Given our incidence assumptions, these are very progressive taxes.

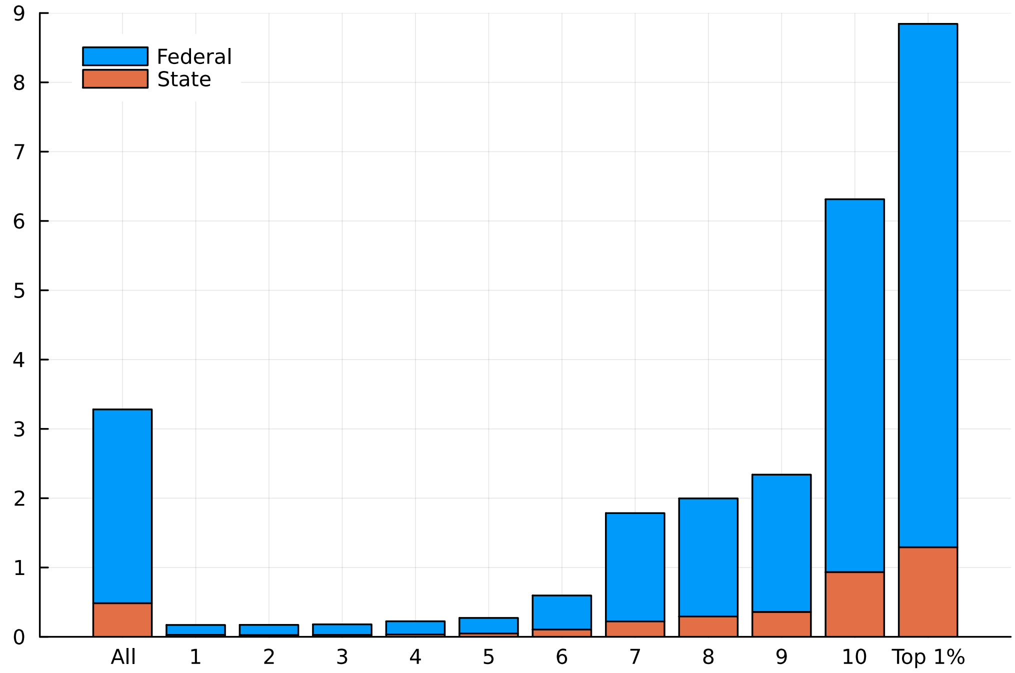

Figure 22: Average corporate income tax rates for 2015/2016. See notes to Figure 1. The tax and income values are reported in Table C1 in Appendix C.2.

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 & 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 CSLG. The state tax on individual business income and the state corporate income 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 (commercial) *property taxes*. To compute the incidence of these two taxes on households, we follow the strategy outlined in the latest edition of the "Minnesota Tax Incidence Study" (Minnesota Department of Revenue, Tax Research Division, 2024).

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 tradables, the price is determined nationally and cannot be raised to accommodate the local tax. The implied tax on labor is applied proportionately to labor income for each household residing in the state. The implied tax on consumer spending is applied proportionately to non-tradable spending of each household residing in the state.

For *property* taxes, in line with our approach in Section 2.3, we assume that the 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 pure rental income in ASEC). The residual share of property tax revenues is treated symmetrically to revenues from taxes on intermediate inputs; that is, we split it into a tradable-share portion falling on workers and a non-tradable portion falling on consumers. Appendix L provides more details.

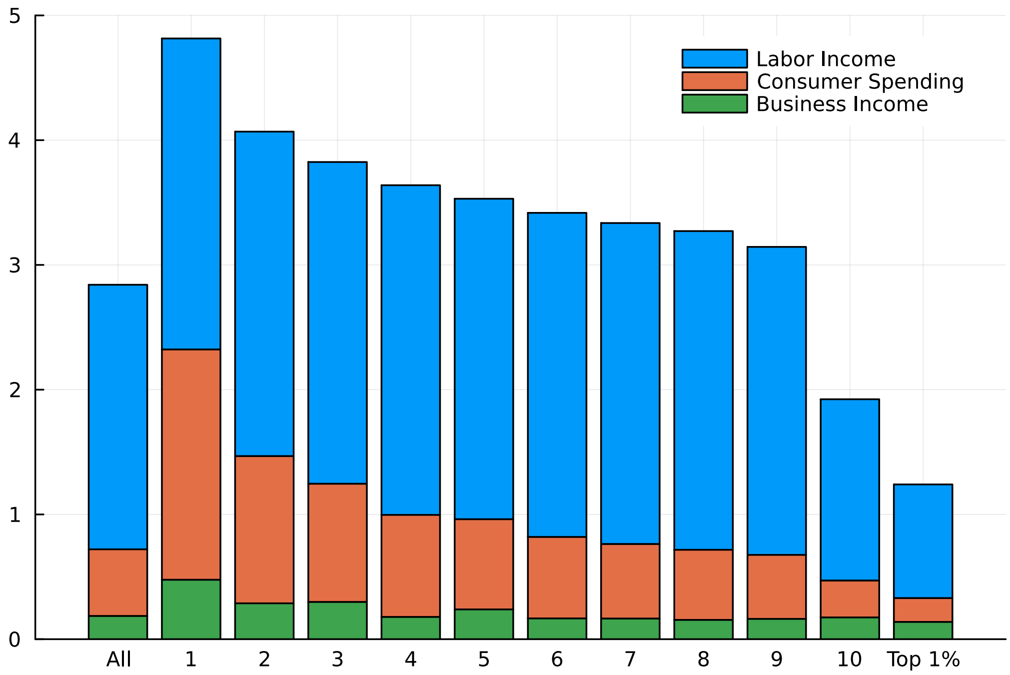

Figure 23: Average business taxes paid for 2015/2016. The plot decomposes taxes by their incidence on labor, consumer spending, and business income (a proxy for commercial property rental income). See notes to Figure 22.

Figure 23 shows the resulting business taxes paid by household income. Given our incidence model, business taxes are regressive, where this regressivity is driven primarily by the fact that part of business taxes raises consumer prices. Those higher prices – just like a sales tax – fall disproportionately on lower income households.

5.2 Extension 2: Spending on Public Goods and Services

States differ substantially in per capita spending on publicly provided goods and services, such as education, transportation and safety (see Appendix M for a summary). To capture the benefits provided to households through these expenditures, we also explore the sensitivity of our results to a more comprehensive notion of transfers. In this "broad" transfer measure, we include all federal, state and local spending on public goods and services.

We present these calculations as an extension, rather than as part of our baseline, because accurately modeling how public spending on different budget items is valued by different households is beyond the scope of this paper. Two main complications arise. First, 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, which 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. Second, 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.[48]

With these caveats in mind, we assess the value of government consumption to households, based on its production costs. For consistency, in this broad measure of progressivity, we also value Medicaid and Medicare receipt to enrollees at 100 percent of the amount spent. We proceed incrementally, and thus in this "broad transfer" extension, we also include the state corporate and business taxes discussed in the previous section.[49]

To construct the broad transfer measure, we collect data on federal spending from the National Income and Product Accounts (NIPA) and data on state and local spending from the CSLG. 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

[48]This logic may also apply to some transfers we included in the baseline measure—for example, Medicaid and food stamps (although food stamps are likely closer substitutes for cash than public health insurance or free schooling).

[49]In Appendix N.2 we report results for an intermediate case in which Medicaid and Medicare receipts to enrollees are valued at 100 percent of the amount spent, but in which we do not include state and local government consumption as part of our transfer measure.

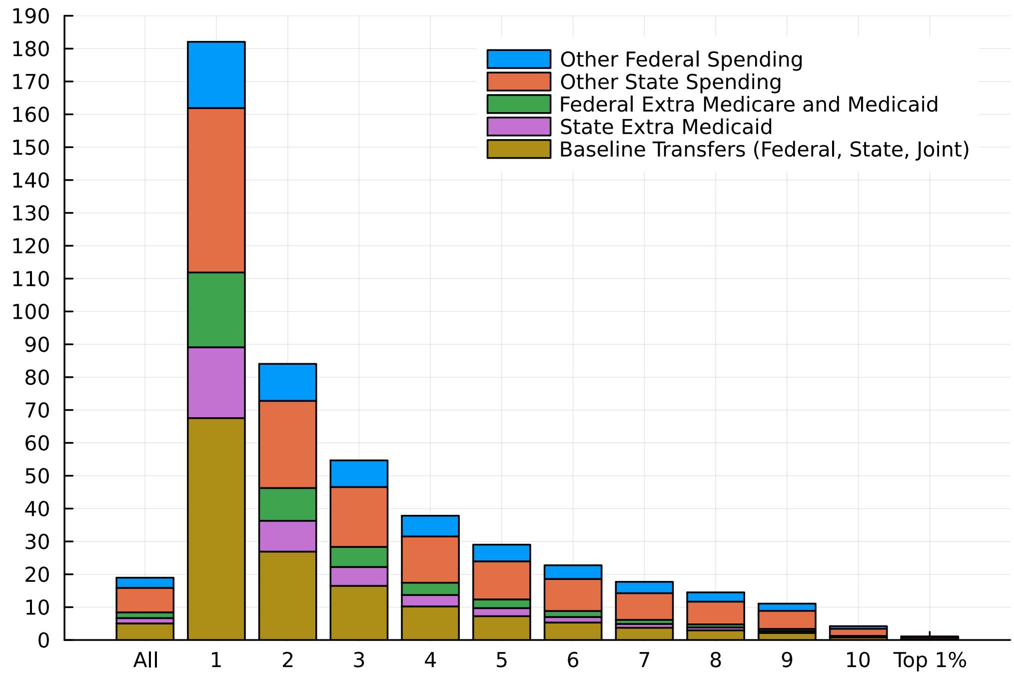

Figure 24: Average transfer rates (as a share of income) for 2015/2016. ”Other Spending” refers to the federal and state spending categories listed in Appendix M. ”Extra Medicare and Medicaid” (for the federal government) and ”Extra Medicaid” (for the state governments) is the difference between the private values included in baseline transfers and total spending. See notes to Figure 22.

fashion across all households (in the state, for state and local expenditures).[50] We subtract from these expenditures revenues from charges that state and local government obtain in exchange of providing services (e.g., airport fees or highway tolls). Appendix M contains a more detailed description of our calculations.

Figure 24 plots average federal and state spending rates, as a share of income, by income decile. ”Other Spending” denotes federal and state spending on public goods and services, while ”Extra Medicare and Medicaid” (or ”Extra Medicaid”) refers to federal (state) spending on these programs that is not already included in the ”Baseline Transfer” measure. The figure illustrates that overall, federal and state average spending on publicly provided goods and services accounts for 11 percent of household income. About 2 percent comes from federal spending and about 9 percent from state spending. By nature of our imputation, both are strongly progressive, and while the state share falls for higher incomes, it always remains larger than the federal share. Federal spending mostly reflects defense and public safety, while state spending is dominated by education.

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

5.3 Results

Aggregate Progressivity The "Extension 1" panel in Table 4 shows that including federal corporate income taxes increases federal progressivity from 0.195 to 0.214, consistent with our description of this tax in Section 5.1. At the state level, we simultaneously add the state corporate income taxes and business taxes, which lowers our progressivity estimate from -0.004 to -0.011. For the aggregate Federal & State estimate, including corporate income and business taxes raises progressivity from 0.202 to 0.227. Recall that we impute federal and state corporate income taxes in a similar manner but federal collections are much larger than state collections.

The "Extension 2" panel in Table 4 reports progressivity estimates, which add our broad transfer measure to the new taxes introduced in Extension 1. This measure includes the differential between total public spending on Medicare and Medicaid and their assumed private values (82 and 40 percent, respectively), as well as 100 percent of the state and federal spending on public goods and services. Moving to the broad transfer measure has a strong positive impact on progressivity, as expected. Overall progressivity, including all federal and state taxes and transfers, is now 0.372, almost double its baseline estimate. Figure 25 illustrates these results.

State Level Average Net Tax Rates Figure 26 shows the effect of including the taxes and transfers in Extensions 1 and 2 on our estimates for state average net tax rates.[51] In all states, including corporate income and business taxes increases the average tax rate markedly. While the average increase is about 3.7 percentage points, this change is much stronger in some states than in others. For example, the rate jumps from 3.1 to 10.2 percent in Wyoming and from 7.1 to 12.1 percent in Mississippi but climbs only from about 9.5 to 11.5 percent in Connecticut and Maryland. When we include the broad transfer measure (Extension 2), net tax rates fall in all states and even become negative in a few states (most notably, Alaska). Again, this difference is much larger in some states, reflecting pronounced differences in both Medicaid and other components of state public spending.[52]

State Level Progressivity Estimates of state progressivity for the baseline specification (see Figure 17) and for Extensions 1 and 2 are shown in Figure 25. As expected, including state corporate income taxes and business taxes (Extension 1) slightly reduces the progressivity estimates relative to the baseline. The reductions are largest in South Dakota, Vermont, North Dakota and Wyoming but are generally similar across all other states, leaving the progressivity

[51] We provide more detailed state-level results for these extensions in Appendix N.
[52] As illustrated by Figure H3 in Appendix H.5 and Figure M1 in Appendix M.2.

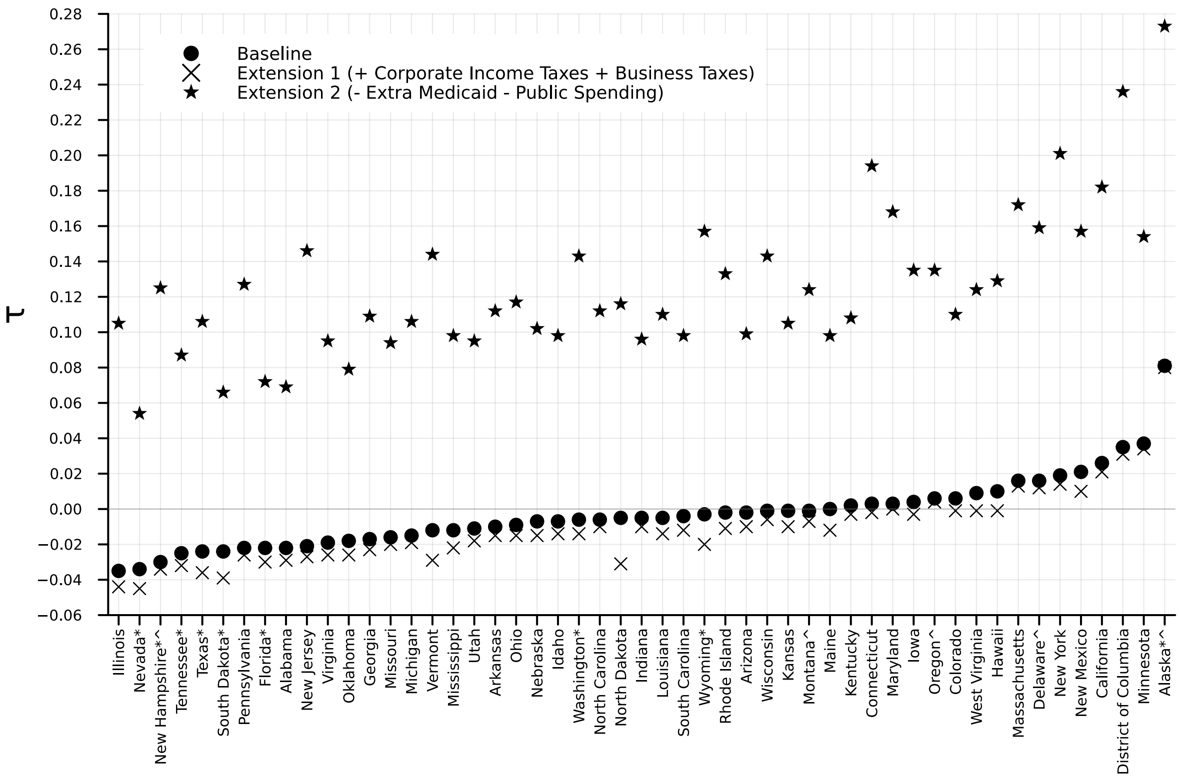

Figure 25: State progressivity. Baseline includes state and local income, excise, sales and property taxes, and the same transfers as in Section 4.3. Extension 1 includes corporate income and business taxes. Extension 2 includes Medicaid valued at full cost (instead of private values) and state spending on public goods and services. See notes to Figure 14. See notes to Figure 17.

ranking of states largely unchanged. Indeed, the Spearman rank correlation coefficient between the Baseline τ estimates and those from Extension 1 is 0.96.

Adding the broad transfer measure in Extension 2 boosts progressivity in all states, and our τ estimates become uniformly positive. Yet, there are strong cross-state differences in the magnitudes of these increases. For instance, the absolute difference in Extension 1 and 2 for Washington, DC, is about 0.205 (from 0.031 to 0.236) but only 0.099 for Nevada (from -0.045 to 0.054). This is because state public spending per capita does not correlate too closely with our baseline and Extension 1 estimates of state tax progressivity. For example, as shown by Figure M1 in Appendix M.2, states like New Jersey, North Dakota, Vermont and Wyoming are among the top spenders but do not belong to the top group of the baseline and Extension 1 progressivity estimates. As a result, the progressivity ranking between states changes substantially, and some states—for example, Minnesota—fall to a relatively lower position. Consistent with this, the rank correlation coefficient between Extension 1 and Extension 2 is only 0.66.

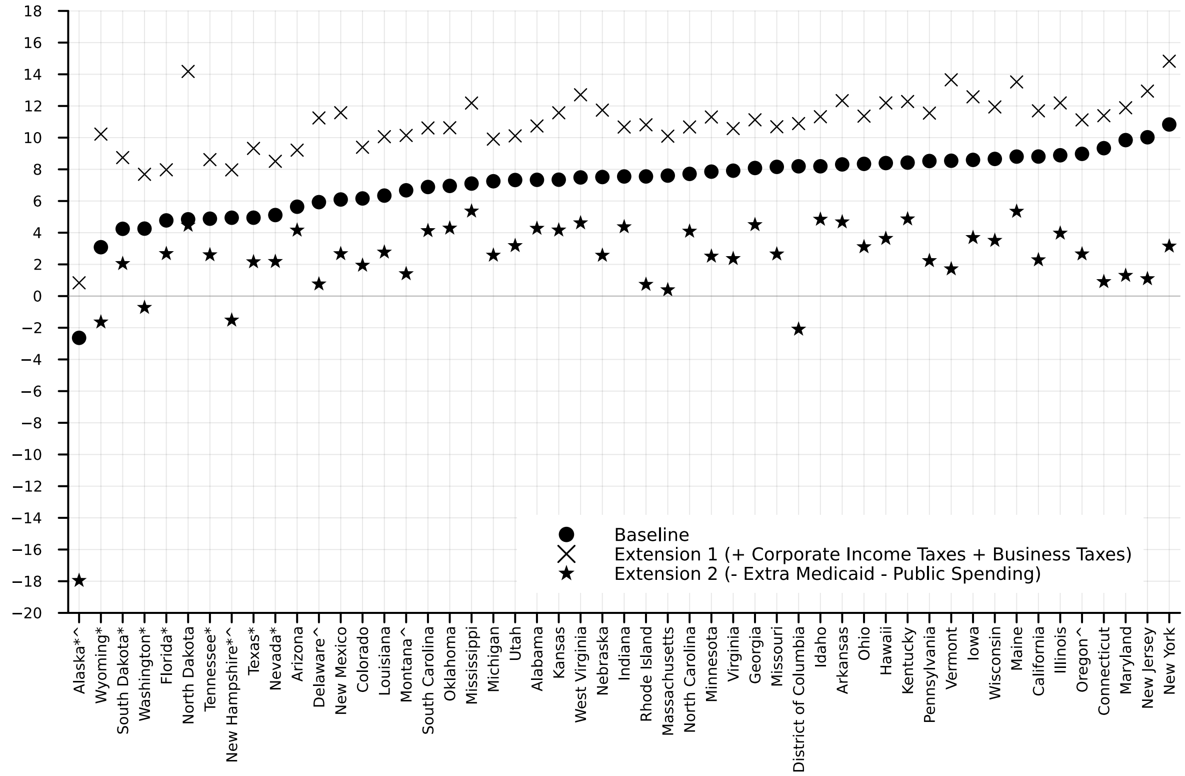

Figure 26: Average tax and transfer rates by state. Baseline includes state and local income, excise, sales and property taxes, and the same transfers as in Section 4.3. Extension 1 includes corporate income and business taxes. Extension 2 includes Medicaid valued at full cost (instead of private values) and state spending on public goods and services. See notes to Figure 14. ASEC sample, 2015/2016.

6 Conclusion

We have measured the progressivity of taxes and transfers for the U.S. federal government as well as for all 50 states and the District of Columbia. Combining several data sources, we constructed comprehensive household-level measures of income, taxes and transfers for the years 2005/06, 2010/11, and 2015/16. We estimated a widely used progressivity measure and found that the federal tax and transfer system is progressive, while state systems are close to proportional, on average.

When we measure progressivity separately for each state, we find sizable differences. Some of these are driven by the choice of the tax base, as states that focus on raising taxes from personal income tend to have progressive tax and transfer systems, while those relying on sales, excise and property taxes tend to have regressive systems. The amount of spending on transfer programs with state options also factors importantly into overall progressivity. Less progressive states tend to have lower average (net) tax rates.

Our finding of large cross-state differences in tax and transfer systems raises the question of why these differences exist. Naturally, U.S. state governments enjoy a large degree of fiscal autonomy regarding choices of tax bases and rates. Another 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. With the exception of Alaska, the states that currently do not impose income taxes or sales taxes are simply the states that never introduced them. The same observation is true for transfer programs with state options; current parameters closely correlate with parameters set many decades ago.

At the same time, however, our estimates of net tax rates and tax progressivity are correlated 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), Altig, Auerbach, Higgins, Koehler, Kotlikoff, Terry, and Ye (2020), Baker, Janas, and Kueng (2020), and Robinson and Tazhitdinova (2023). Do politically progressive voters drive the implementation of progressive tax systems, as in Stantcheva (2021)? Or does the experience of living with progressive tax systems make voters more left-leaning, as in Piketty (1995) and Hassler, Rodriguez Mora, Storesletten, and Zilibotti (2005)?

Our estimates could be used to investigate the role of cross state variation in tax systems in driving migration decisions and state population growth. Higher state taxes should discourage net migration into a state, unless the associated higher state spending is sufficiently valued. The implications of tax *progressivity* for migration are more nuanced. One might expect a more progressive state tax and transfer system to repel high-income households but to attract low-income households. In fact, we find that inter-state migrants at all income levels tend to move to less progressive states, but this is especially true for moving households at the top of the income distribution. Of course, this is just a correlation: more structural work is required to isolate the causal impact of tax progressivity on migration choices.

Another set of important questions concerns the implications of differences in tax rates and tax progressivity for economic performance at the state level. 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. Akcigit, Grigsby, Nicholas, and Stantcheva (2022) focus on the negative effect of higher state taxes on innovation. We hope our measurements will prove useful for researchers working on these and other topics.

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Appendix

The appendix to ”Fiscal Progressivity of the U.S. Federal and State Governments” (Fleck, Heathcote, Storesletten, Violante, December 2024) is organized as follows:

- Section A provides an overview on the size and composition of state and local tax collections.
- Section B explains for which ASEC households we use income and tax information from the IRS-SOI state tables.
- Section C presents summary statistics from the SOI augmented ASEC dataset and our baseline sample.
- Sections D, E and F contain detailed explanations on the measurement and imputation of federal and state income, sales, excise and property taxes, respectively.
- Section G compares the imputed state tax revenues to external benchmarks.
- Section H explains the measurement and imputation of federal and state transfers.
- Section I documents the methodology we use to align state income distributions before estimating state specific tax and transfer progressivity.
- Section J provides additional results on our baseline estimates of state progressivity.
- Sections K and L explain the measurement and imputation of federal and state corporate income taxes and business taxes.
- Section M explains the measurement and imputation of federal and state spending as a household transfer.
- Section N provides additional results on our extended estimates of state progressivity.
- Section O discusses alternative progressivity measures and estimation strategies.

A State and Local Taxes

A.1 Size and Composition

Figure A1 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.[53] 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 percent (in Alaska) to 11.6 percent in New York, Maine and Vermont.

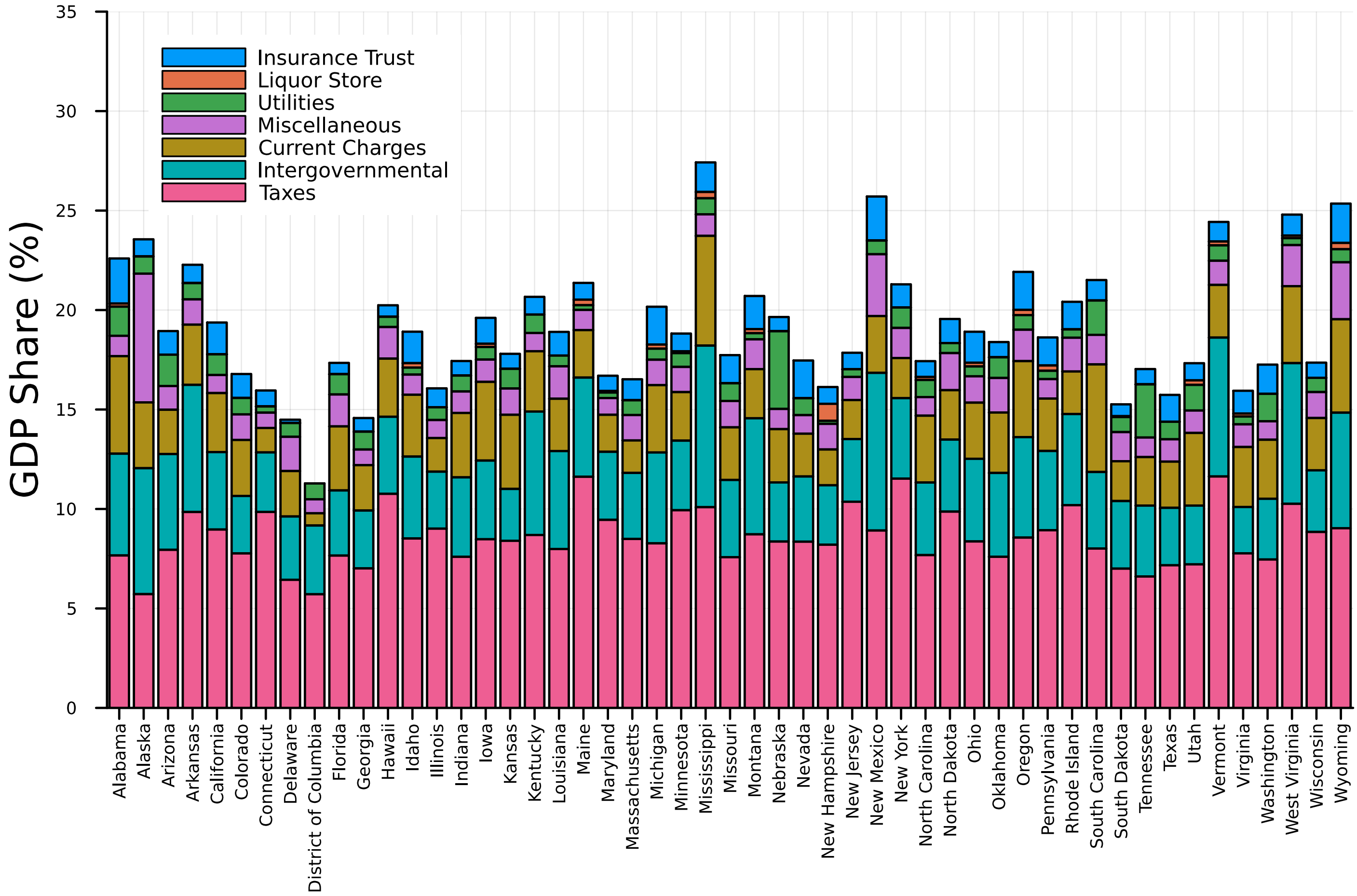

Figure A1: State and Local Total Revenues as Shares of State GDP (2016). Source: Census of State and Local Governments (CSLG) and Bureau of Regional Analysis (BEA).

A.2 State vs. Local Taxes

In Figure A2, 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 percent of state GDP, on average. They are almost exclusively levied by local governments (a notable exception is Vermont).

[53] "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, and parks and recreation, among others. "Intergovernmental" refers to funds received from the federal government (through grants, shared taxes, or reimbursements) to support state programs and services. See Census Bureau (2006) for details.

Sales taxes are collected in most states, and **excise taxes** are collected in all states. They are collected mostly at the state level and are state governments' most important source of tax revenue, averaging about 3 percent of state GDP.

Individual income is untaxed in a few states (Alaska, Florida, Nevada, South Dakota, Texas, Tennessee, Washington, Wyoming). In states where it is taxed, income taxes represent about 2 percent of GDP, on average. Income is generally taxed at the state level, but there are also local income taxes in some states.[54]

Corporate income taxes are a minor source of tax revenue for all state and local governments, representing about 0.2 percent of state GDP, on average. They are collected only at the state level, except in New York (and DC).

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).

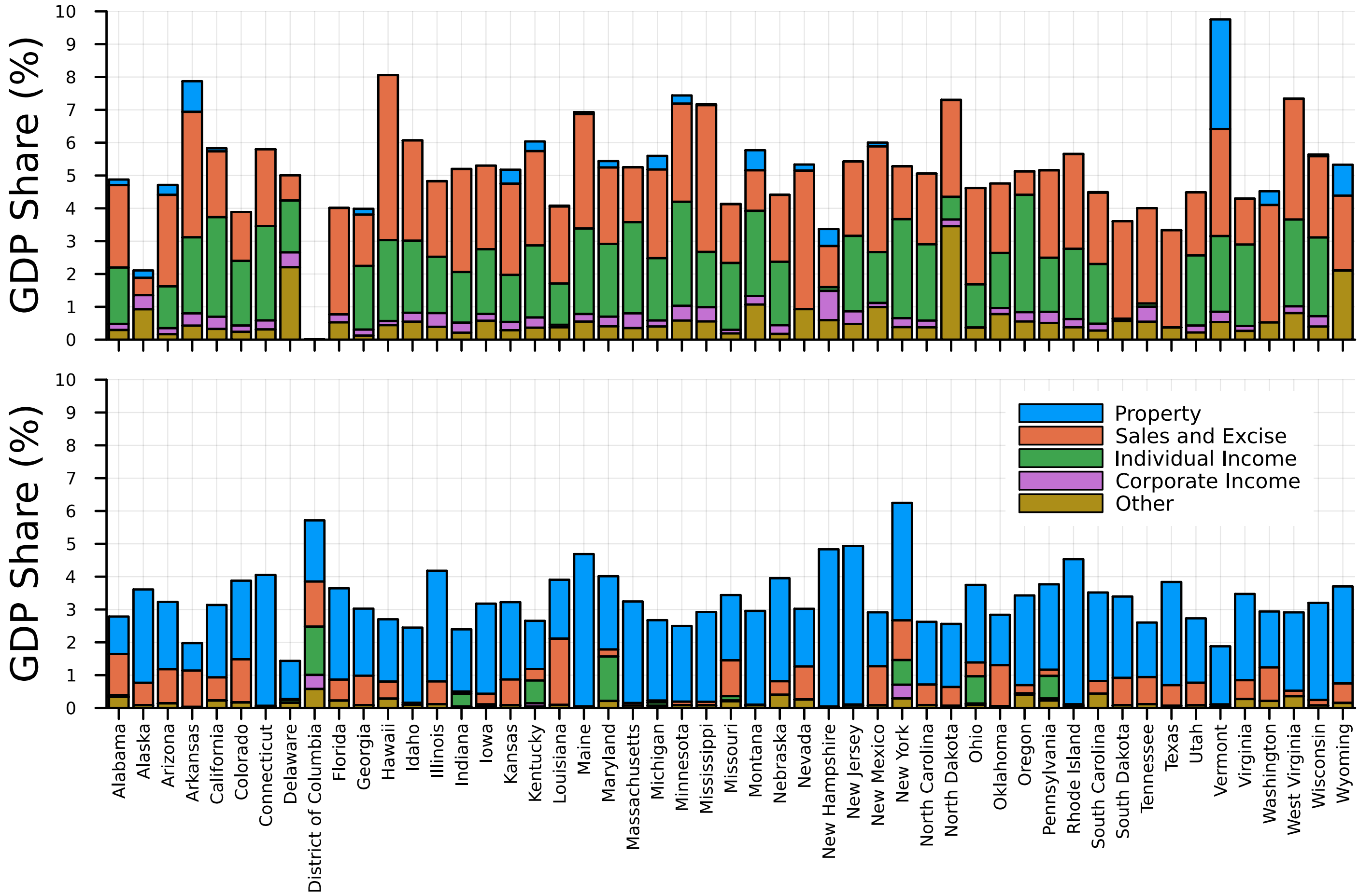

Figure A2: Top Panel: State Tax Revenues as Shares of State GDP (2016). Bottom Panel: Local Tax Revenues as Shares of State GDP (2016). Source: CSLG and BEA.

A.3 Tax Collections from Households vs. Businesses

State and local governments collect taxes from households and businesses. According to Ernst & 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

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

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 A1 (pink) into those collected from households (green) and businesses (orange) in Figure A3.

On average, the business share is 46 percent—that is, about half of all state and local taxes were collected from businesses. However, cross state variation is sizable, and shares range from 30 to 75 percent. In general, the share is highest (above 60 percent) in states with activity in resource extraction (Alaska, North Dakota, Texas and Wyoming) and lowest (below 40 percent) 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 5.1 and appendix L.

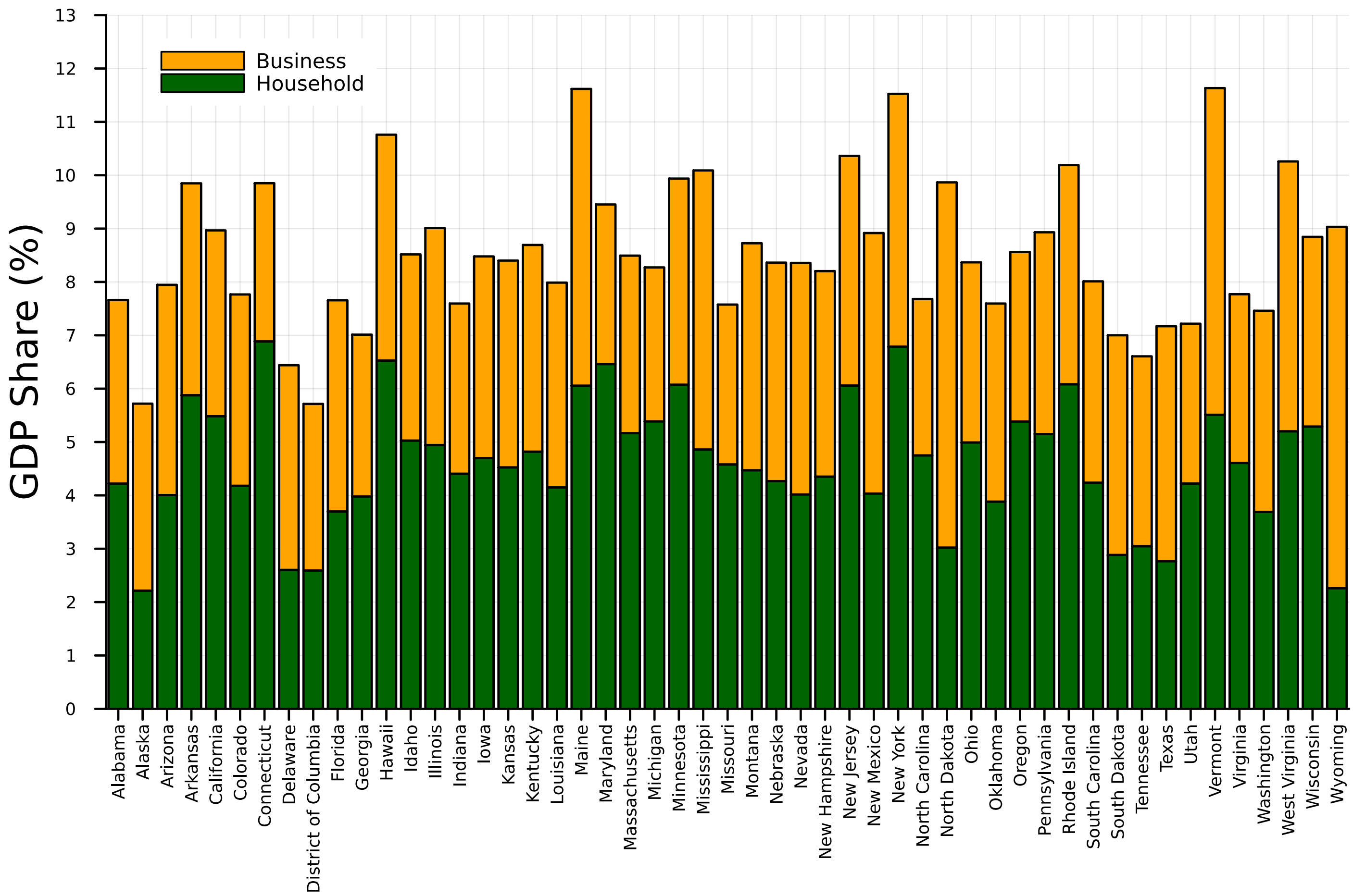

Figure A3: State and Local Total Tax Revenues from Businesses and Households as Shares of State GDP (2016). Source: CSLG, BEA and Ernst & Young (2016).

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).[55] The Average Replacement Value method replaces self-reported incomes that 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 years 2005 and 2006 but unrestricted in later sample years.

Because of 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 than 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 us 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

$$y_i = \sum_{j=1}^{J} \sum_{k=1}^{K} y_{j,k} \tag{B1}$$

where i denotes households, j indexes household i's members, k is 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,

$$y_{j,k} = \begin{cases} y^*_{j,k} & \text{if } y^*_{j,k} < \overline{y}_k \\ \tilde{y}_{j,k} & \text{if } y^*_{j,k} \geq \overline{y}_k \end{cases} \tag{B2}$$

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,

$$y_{j,k} = \begin{cases} y^*_{j,k} & \text{if } y^*_{j,k} < \overline{Y}_k \\ \overline{Y}_k & \text{if } y^*_{j,k} \geq \overline{Y}_k \end{cases} \tag{B3}$$

[55] 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.

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

$$\underline{y}_i = \sum_{j=1}^{J} \left\{ \underbrace{\sum_{k=1}^{\underline{K}} y_{j,k} | y_{j,k} < \overline{y}_k}_{\text{unmodified income categories}} + \underbrace{\sum_{k=1}^{\overline{K}} \overline{y}_k | y_{j,k} \geq \overline{y}_k}_{\text{modified income categories}} + \underbrace{\sum_{k=1}^{\widehat{K}} y_{j,k}}_{\text{topcoded income categories}} \right\} \leq y_i \tag{B4}$$

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, the data provide averages of individual total incomes and taxes paid for different bins of adjusted gross income (AGI) in each state.[56] 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.[57] 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 us to construct a corresponding income measure by subtracting unemployment compensation and taxable social security benefits from total income and adding the employer FICA contribution.[58]

We use the SOI data to replace the incomes and taxes of ASEC households that 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 that 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 percent of tax filers itemized deductions instead

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

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

[58]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.

of choosing the standard deduction. Thus, this income threshold gives us reasonable measures of state and local income taxes as well as property taxes.[59]

For the entire dataset in 2015/2016, the share of SOI replaced households is 5.4 percent. For reference, the share of tax returns with AGI above $200,000 is 4.6 percent.[60] We report the total and by income decile replaced share in the tables in Appendix C.

B.3 Taxes Paid by High Income Households

Figure B1 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 that 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, which reflects their inability to deduct state taxes on federal returns.

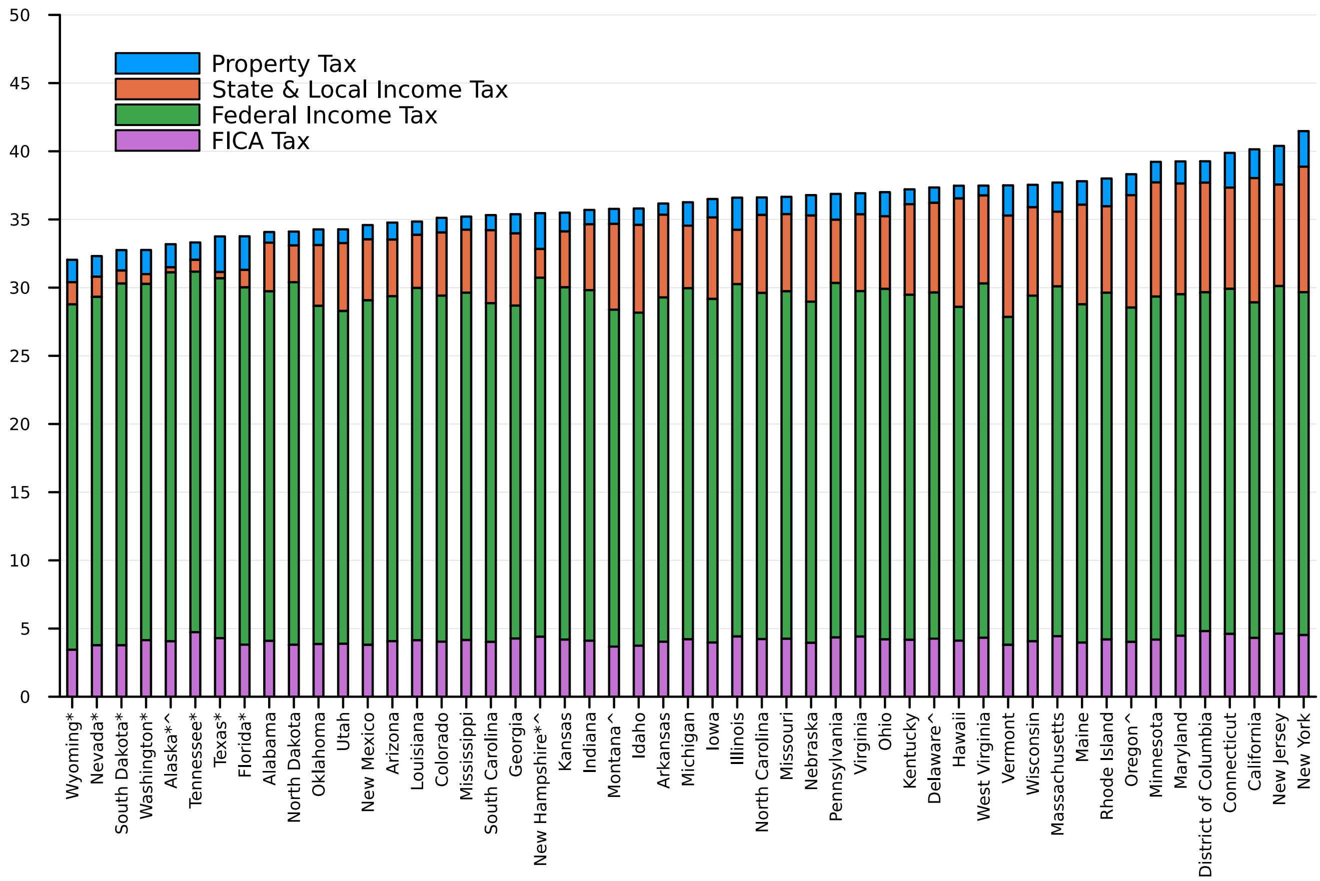

Figure B1: Taxes and transfers as a percentage of adjusted gross income (AGI) for households with AGI between $500,000 and $1,000,000 by state. Source: IRS SOI state tables 2016. States without income tax are marked with an asterisk. According to the SOI, households with AGI in this range that reside in states with no income tax earn (some) income in states where it is taxable.

[59]This share of itemizers declined substantially from 2018—that is, 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.

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

C Household Data: 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 that provides us with a reasonable number of households after applying our sample selection conditions. Figure C1 shows that for all of our sample years, we have no fewer than 500 households in each state in our sample (without applying ASEC household weights).

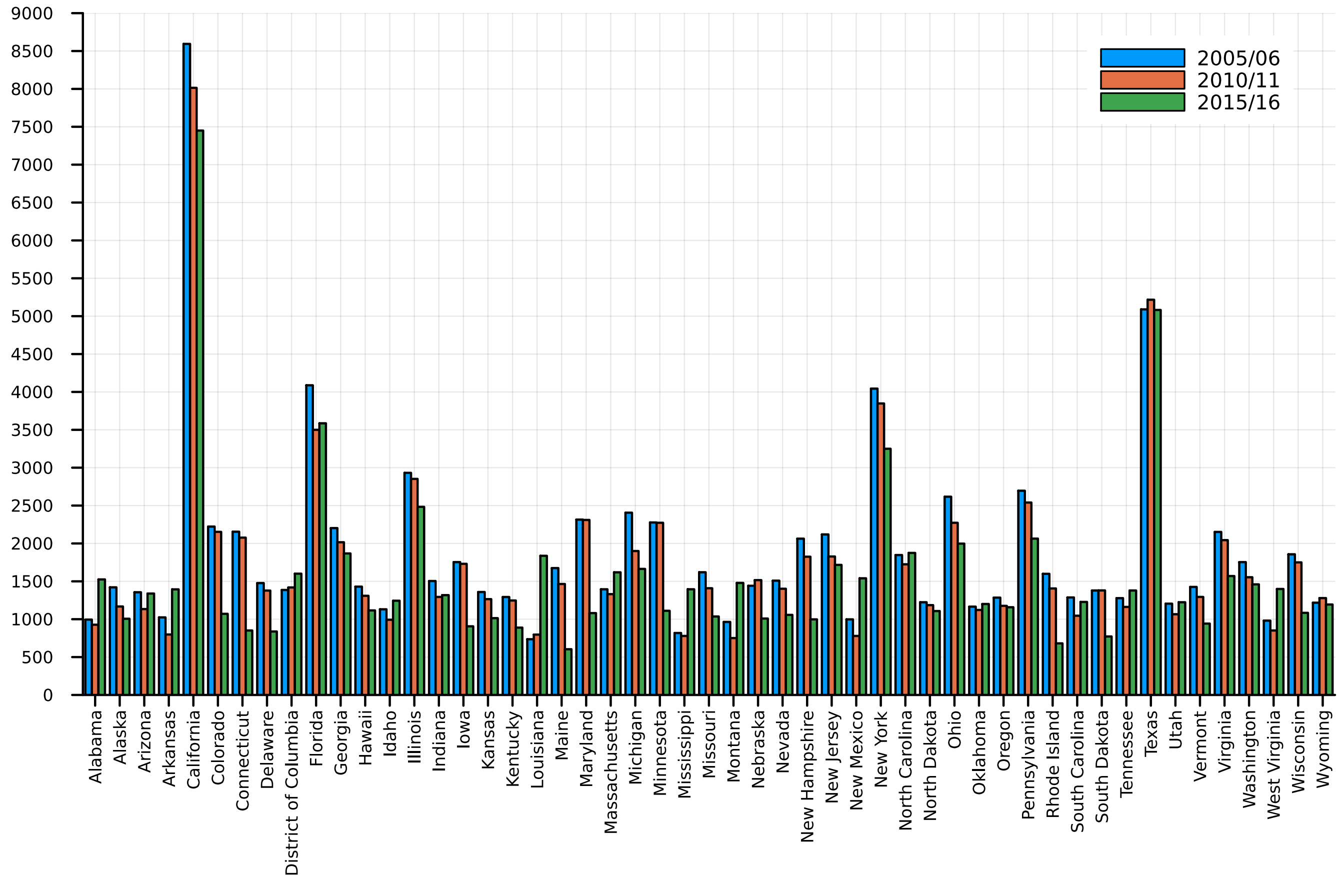

Figure C1: Households by state in the ASEC baseline sample. This sample selects households with heads aged between 25 and 60 and one spouse having at least part-time minimum-wage labor earnings.

C.2 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 C1: 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). Column "All" reports average income and tax and transfer values for the entire sample. Columns 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. Column "Top 1%" refers to the one percent of households with the highest incomes. All variables are in current $ unless indicated otherwise. "HH size" reports number of persons, "HH head age" reports years, and "N, unweighted" and "N, ASEC weights" report numbers 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.

C.3 Full 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 C2: Distribution of income, taxes, and transfers in the ASEC dataset, 2015/2016. Numbers have been computed using ASEC household weights. Column "All" reports average income and tax and transfer values for the entire sample. Columns 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. Column "Top 1%" refers to the one percent of households with the highest incomes. All variables are in current $ unless indicated otherwise. "HH size" reports number of persons, "HH head age" reports years, and "N, unweighted" and "N, ASEC weights" report numbers 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.

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 that impose them. Average local tax rates range up to 2.3 percent in Maryland (where all counties collect them). As illustrated by Figure A2 in Section A, they accounted for more than 10 percent 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 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).[61] We use these imputed amounts for non-SOI-replaced 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 CSLG, 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.[62]

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

E Consumption Taxes

This section lays out our approach for imputing consumption taxes. We impute these taxes as consumption expenditures times 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 using data from the Consumption Expenditure Survey (CEX). We categorize goods as follows: (1) food at home; (2) food away from home; (3) alcohol; (4) maintenance, repairs, other expenses (excluding insurance) related to the residence; (5) other lodging; (6) utilities, fuels and public services; (7) housekeeping supplies; (8) house-

[61] 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.

[62] 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).

hold 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;[63] (19) household operations; (20) miscellaneous; and (21) other. Each of these categories are subject to different excise or sales taxes. All goods and services that are not subject to any sales or excise taxes are lumped together in category 21 ("Other").

The CEX reports tabulated average consumption expenditures for each good for different household income bins. For each income bin $n \in \{1, ..., N\}$, 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 $y \in [\bar{y}_1, \bar{y}_N]$. Outside of the extreme points, $y < \bar{y}_1$ and $y > \bar{y}_N$, we do log-linear extrapolation for incomes larger than $\bar{y}_N$ and we assign $\bar{y}_1$ to incomes below this point.

We scale the CEX-based consumption imputation by aggregate consumption of good j as recorded in the Personal Consumption Expenditures (PCE) of the Bureau of Economic Analysis (BEA). The purpose is to correct for good-specific under-reporting in CEX (Garner, Janini, Paszkiewicz, and Vendemia, 2006). By scaling aggregate consumption, we aim to enlarge the consumption tax base, which helps to impute all of the consumption tax revenue. The imputed consumption function is then

$$c_{jt}^{IMP}(y) \equiv \frac{C_{jt}^{BEA}}{C_{jt}^{CEX}} \cdot c_{jt}^{CEX}(y), \tag{E1}$$

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. To calculate C_{jt}^{CEX}, we assign the household consumption functions we estimated using CEX data into the ASEC dataset (modified by the SOI sample) by merging on state, year, and nearest household incomes. This allows us to compute C_{jt}^{CEX} using the income distribution reported in ASEC so that $C_{jt}^{CEX} = \sum_{i=1}^{I} \omega_i \cdot c_{jt}^{CEX}(y_i)$, where the sum is taken over all households in ASEC and ω_i represents the ASEC weight for household i. Table E1 reports the adjustment factors $C_{jt}^{BEA}/C_{jt}^{CEX}$ for 2016.[64]

	(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 E1: This table reports the consumption adjustment factors calculated as the ratio of aggregate consumption for various goods according to the BEA's Personal Consumption Expenditure and the CEX/ASEC. The latter is computed using the consumption function $c^{CEX}(y)$ evaluated at the households income levels in the ASEC dataset (modified by SOI data for topcoded incomes). The consumption categories are listed above.

Imputing average consumption taxes for excise-tax goods: We impute average consumption taxes for excise-taxable goods and services according to aggregate consumption and tax revenue. We focus on excise taxes for the following six goods and services: tobacco, alcohol, motor fuels, public utilities, amusements, and insurance.

[63]Insurance comprises homeowners insurance, vehicle insurance, health insurance (paid by households), and life and other personal insurance.

[64]We do this adjustment only for the categories we can match to PCE. Hence, we can 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.

We retrieve total state and local revenue from excise and sales taxes on each of these goods and services for each state and year, T_{sjt}, from the Census of State and Local Governments (CSLG) – 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 FRED. For states where alcohol is sold via liquor stores, we add to the sales and excise tax revenue from alcohol sales the net revenue from state liquor stores net of expenses which is available from the CSLG.

As the CSLG reports tax collections from households and businesses, 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 or service j paid by households. For tobacco products, amusements, alcoholic beverages, 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 $\phi_{gasoline} = \frac{2}{3}$ paid by households. For public utilities, we assume the same split as for motor fuel, $\phi_{utilities} = \frac{2}{3}$.

We calculate average sales and excise tax rates for the excise taxable good or service j in state s in period t according to tax revenue and the spending aggregates reported by the BEA. We define the tax rates with the imputed aggregate net-of-tax consumption, denoted C^{pretax}_{jst}, as the base. The federal tax rate can then be calculated as

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

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

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

Finally, we impute sales and excise taxes for excise taxable good or service j in year t for a household in state s with ASEC income y_{is}, using the average tax rates and the imputed consumption function from equation (E1), as

$$T^{Ex}_{ijst} = \frac{t_{jst} + t_{jFt}}{1 + t_{jFt} + t_{jst}} \cdot c^{IMP}_{jt} \left(y_{is}\right). \tag{E2}$$

Sales taxes on non-excise taxable goods and services: The Tax Foundation reports, for every year and state, statutory sales tax rates τ^{SALES}_{jst}, which 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 exempt items such as 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 from the Tax Foundation is 2009 (Padgitt, 2009). Hence for 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 in year t is then the sum over all goods and services:

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

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.[65] 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 percent of all owners are top-coded. Moreover, as shown in Figure F1, 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.

Furthermore, as the left panel of Figure F2 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 percent 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.[66] 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 F2 illustrates, top-codes for house value are less restrictive: in the 2015/16 baseline sample, only 0.84 percent of all household values are top-coded.[67] Moreover, almost all top-coded households are in the highest income group, where their share is just below 8 percent.

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).[68] 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 $t_{s,t}^{p}$.

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

[66] As shown in Table C1 in Appendix C, we use IRS-SOI property tax data for about 60 percent of ASEC households in the highest income decile.

[67] Until 2007, the ACS house value top-code is $1m. For later years, it is state specific.

[68] The share of households that report property taxes larger than house values is about 0.2 percent in the baseline sample (2015/16).

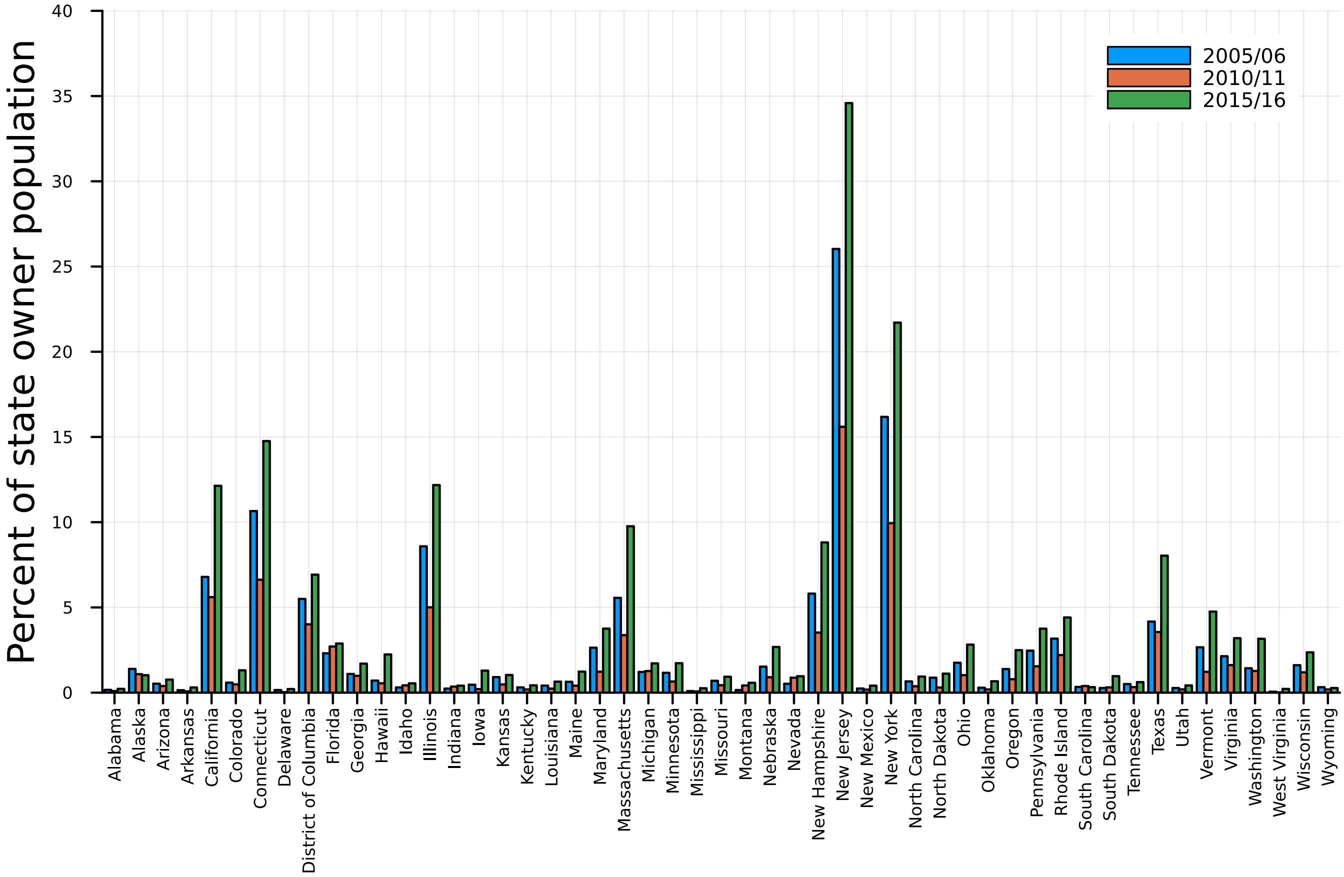

Figure F1: Share of ACS home owners with reported property taxes at the top-code ($10,000). Computed using the baseline selection conditions and ACS household weights. Refers to 2015/2016.

Next, we match ASEC owners to ACS owners. First, we identify as many counties as possible in the ACS using PUMA-county equivalency files.[69] 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 which 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.[70]

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 an approach similar to the one we use 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

[69] We proceed as described here: https://blog.popdata.org/ipums-faqs-missing-u-s-counties/

[70] 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.

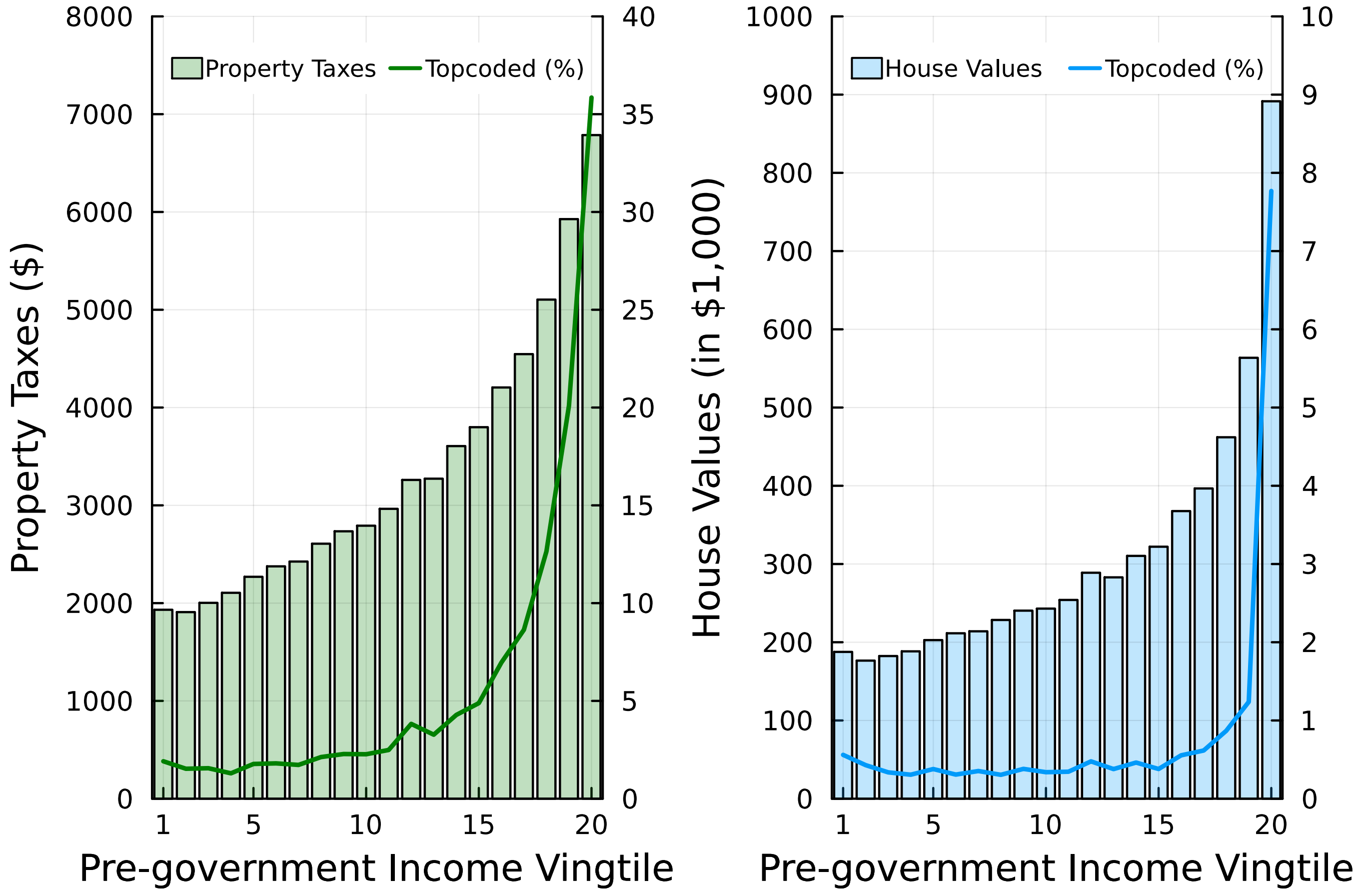

Figure F2: Left panel shows mean property taxes (left) and share at top-code (right) by income vingtile for the baseline sample. Right panel shows analogous means for house values. Source: ACS (2015/2016)

payments and county (state) specific price-rent ratios:

$$P_{i,c,t} = \text{Gross Rent}_{i,c,t} \times \beta_{c,t}, \tag{F1}$$

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 available at the county and state level only 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:

$$T_{i,c,t} = P_{i,c,t} \times t^p_{s,t} \tag{F2}$$

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 $\gamma_{c,t}$:

$$\text{Renter Property Taxes}_{i,c,t} = \gamma_{c,t} \times T_{i,c,t}. \tag{F3}$$

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 is passed on to tenants in the form of higher rent, as given by equation (1) and used in equation (F3). 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, we see that 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, we get that

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

and

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

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, we see that

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

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 the following 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).[71]

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

Figure F3 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 percent).

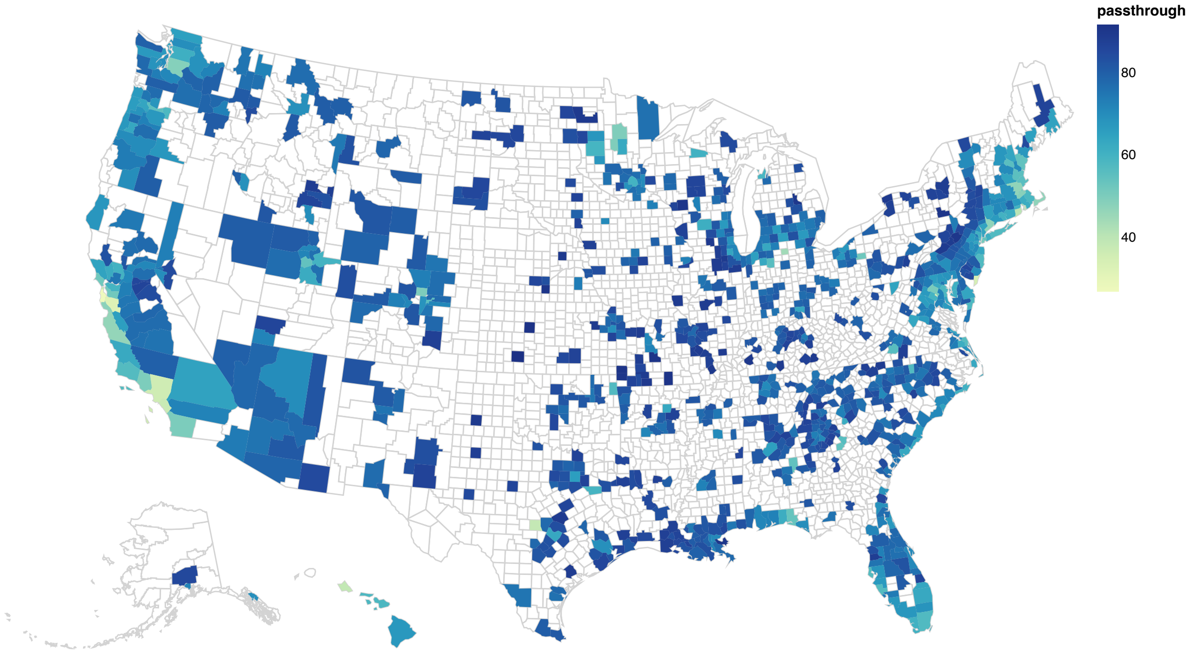

Figure F3: Property tax pass-through for renters by county, in percent. Computed as described in Appendix F.3 using 2012-2017 ACS multi-year data.

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 (F4) summarizes the main determinants of property taxes paid by household i on property j in year t in locality c:

$$T^P_{j,c,t,i} = \min\left\{ cb_{c,t} \times y_{c,t,i} \,,\, \left(\sum_{j=1}^{K} t^P_{t,c,k} \times \left(asr_{j,c,t} \times apr_{j,c,t} \times V_{j,c,t} - E_{j,c,t,i} \right) \right) - TC_{c,t,i} \right\} \tag{F4}$$

Note that except for household income y and property value V, all right-hand-side variables are determined by policy parameters that we now explain in detail.[72]

As a first step in the property tax determination process, a property's taxable value needs to be established. The

[72] 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.

equation's innermost term shows the variables and parameters critical to this first step:

$$asr_{j,c,t} \times apr_{j,c,t} \times V_{j,c,t} - E_{j,c,t,i}. \tag{F5}$$

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, W.J., G. C. Cornia, and L. C. Walters (eds.), there is a wide range of methodologies in use by different jurisdictions. Some rely on computer assisted mass appraisal methods, while others apply a judgmental 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. Lincoln Institute of Land Policy and Minnesota Center for Fiscal Excellence (2018) document that assessment ratios vary considerably across and within states states. Some state or local governments impose 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 that 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 National Association of Counties (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 or 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:

$$t^P_{j,c,t} = \sum_{k=1}^{K} t^P_{c,t,k}. \tag{F6}$$

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.[73]

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.[74]

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

[73] 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.

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

earners or retirees, by restricting property tax liabilities to a certain share of income:

$$T^P_{j,c,t,i} = \min\Big\{cb_{c,t} \times y_{c,t,i}, \text{Property Taxes After Credits}\Big\}, \tag{F7}$$

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 and disability and surviving spouse status.

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, C1 and C2, 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).[75] Answering this question from an empirical perspective is challenging, because as illustrated by equation (F4), 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 observe only owners' self-reported property taxes T^P_i, 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):

$$\frac{T^P_i}{y_i} = \frac{V_i}{y_i} \times \frac{T^P_i}{V_i}. \tag{F8}$$

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

[75] Some recent contributions are Oates and Fischel (2016), Levinson (2021), 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.

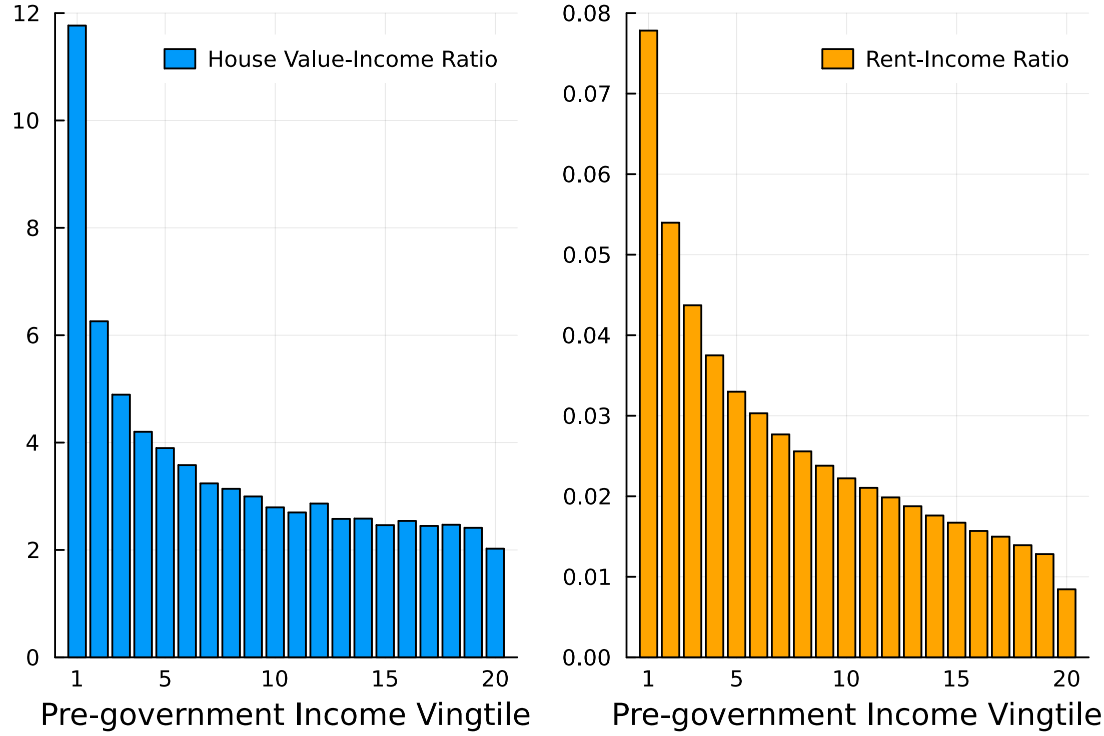

Figure F4: House value-income ratios (for owners; left) and gross rent-income ratios (for renters; right) by pre-government income. Each bar represents mean house values (rents) divided by mean pre-government income for each income vingtile, where households are ranked according to income. Source: ACS (2015/2016).

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 F4 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 8 percent of their annual income in monthly rent.[76] For households with the highest incomes, this share is less than 1 percent.

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 F5 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 percent for all income groups (and markedly lower only for the highest income group). The mean rate, however, declines from about 1.6 percent for households in the lowest income group to about 1.1 percent

[76]Note that the income measure used here refers to pre-government income; i.e., it excludes any transfers and tax credits.

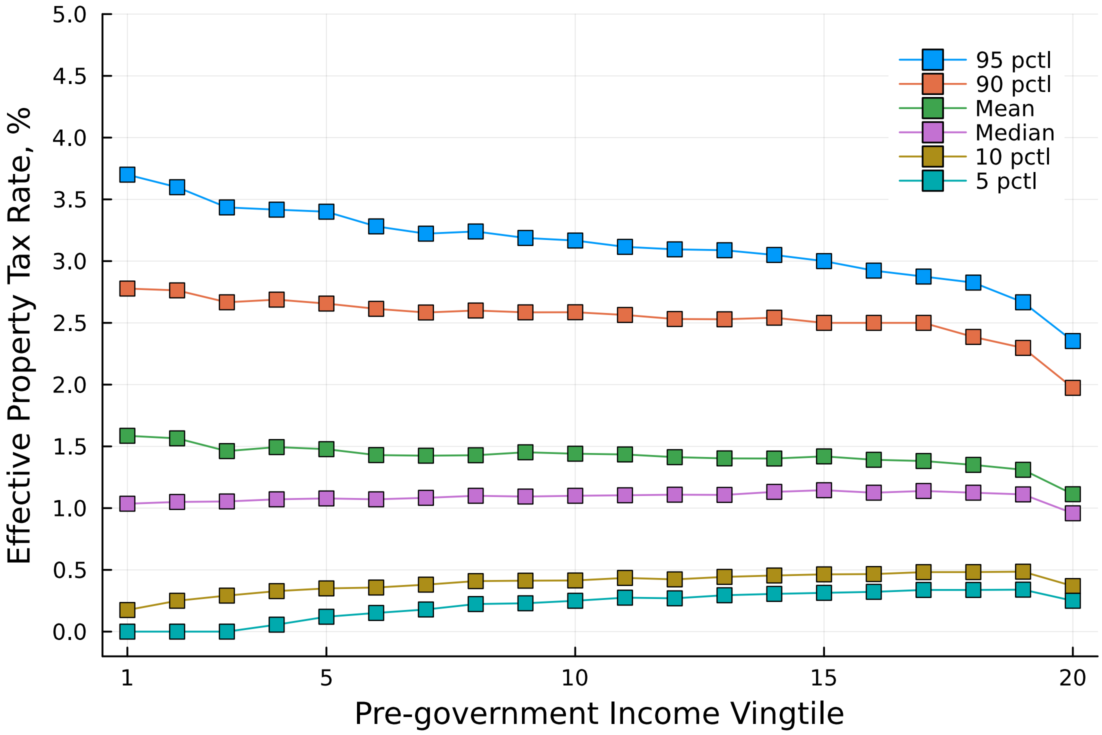

Figure F5: Mean effective property tax rates of owners in different income vingtiles (as well as mean and median), where households are ranked according to pre-government income. Source: ACS (2015/2016).

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 percent for the lowest income group and then declines to about 2.4 percent 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.[77] Households in the highest income vingtile seem to pay markedly lower effective property tax rates throughout the distribution.

To understand why effective property taxes are lowest for households with the highest incomes, Figure F6 separately plots the numerator and denominator (property taxes and house values) used to compute these rates. As previously illustrated by Figure F2, both of these ACS variables have distinct top-codes, and property taxes are more restricted. Importantly, in the highest income vingtile, about 35 percent of ACS owners are at the property tax topcode, while less than 8 percent are at the house value topcode. Figure F6 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 percent (from \$580,000 to about \$900,000) on average, while property taxes increase by only 15 percent (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

[77]Recall that our baseline sample excludes retirees.

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.

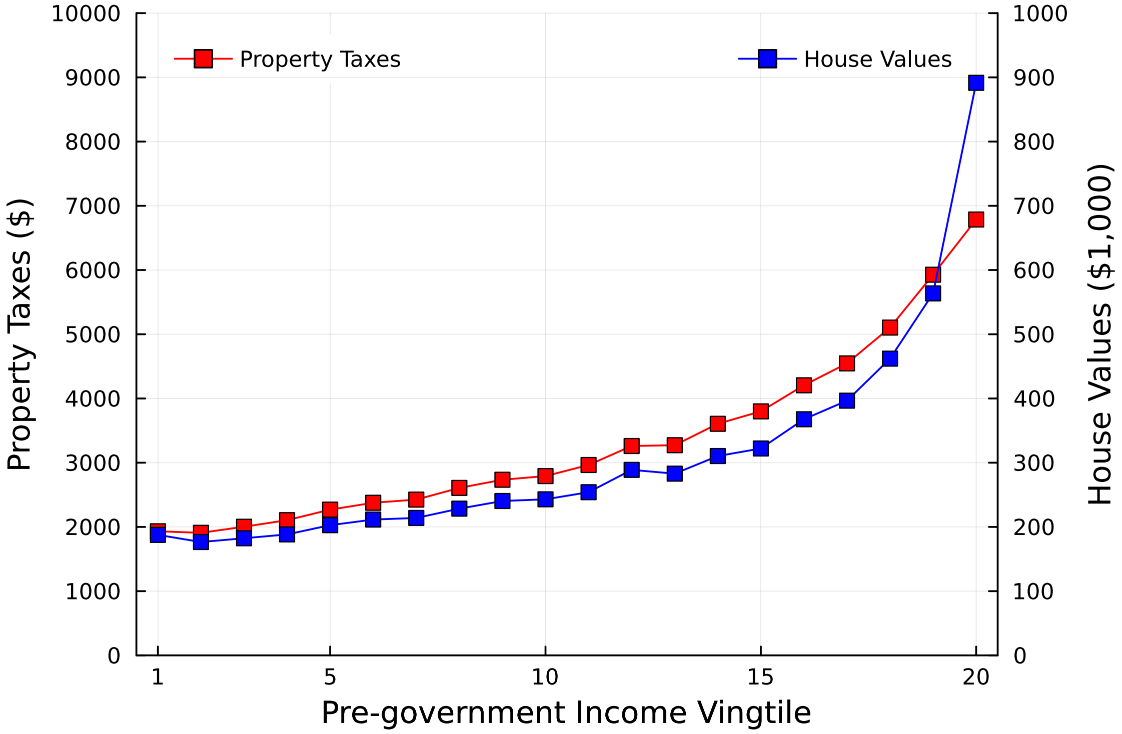

Figure F6: Mean property taxes (left) and house values (right, in $1,000) for ACS owner household in the baseline sample by income vingtile, where households are ranked according to pre-government income. Source: ACS (2015/2016).

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 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.[78] 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 percent of the households selected using the baseline conditions are top-coded in 2015 (as opposed to 6 percent in the ACS baseline sample of 2015/2016).

However, unlike the ACS, the AHS public use file provides no information on county or state of residence.[79] 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 F7. 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 F7 gives us confidence that our ACS-based property tax estimates accurately capture the extent of regressivity embedded in how property is taxed.

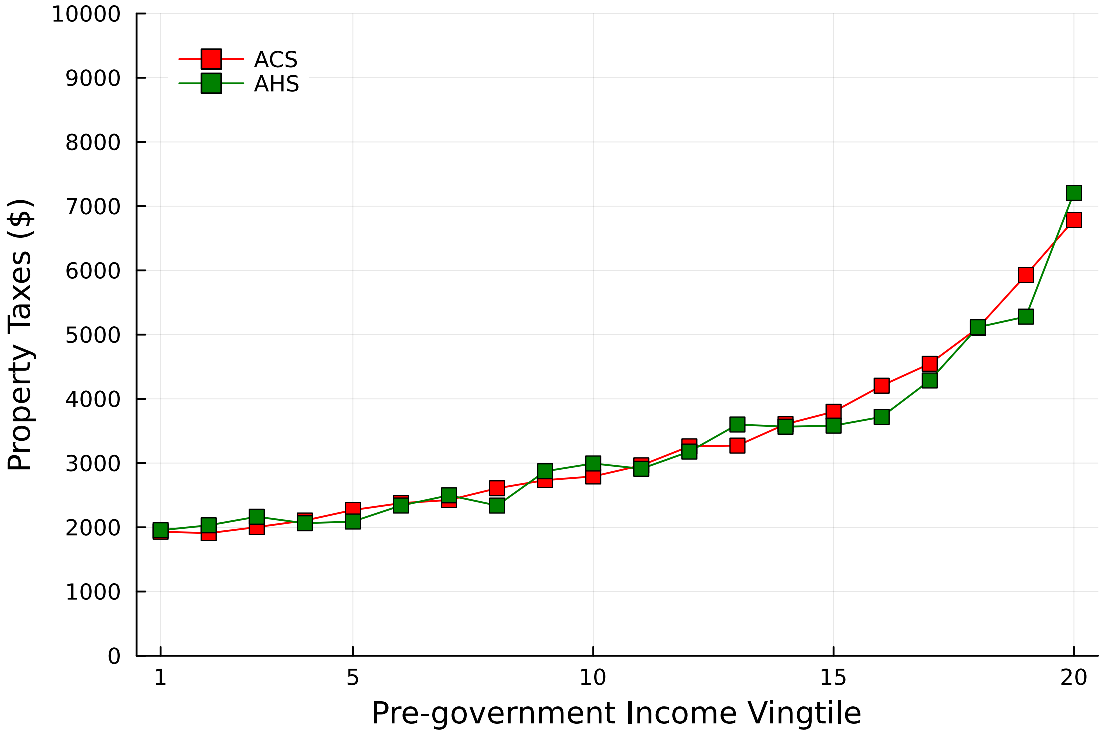

Figure F7: ACS and AHS mean property taxes by income vingtile using the baseline sample selection conditions. ACS (2015/2016), AHS (2015)

G States Tax Revenues: Imputations 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 with

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

[79] Before 2015, the only available geographic indicator in the AHS Public Use File is the Metropolitan Statistical Area (MSA). Yet, 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 provides only core based statistical area (CBSA) and Census Division identifiers.

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 state resident tax collections using population data from the Census Bureau's Population Intercensal Estimates tables.[80]

Income Taxes Figure G1 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 that 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 those in the CSLG: DC has especially many (high-income) households with income tax obligations in other states.

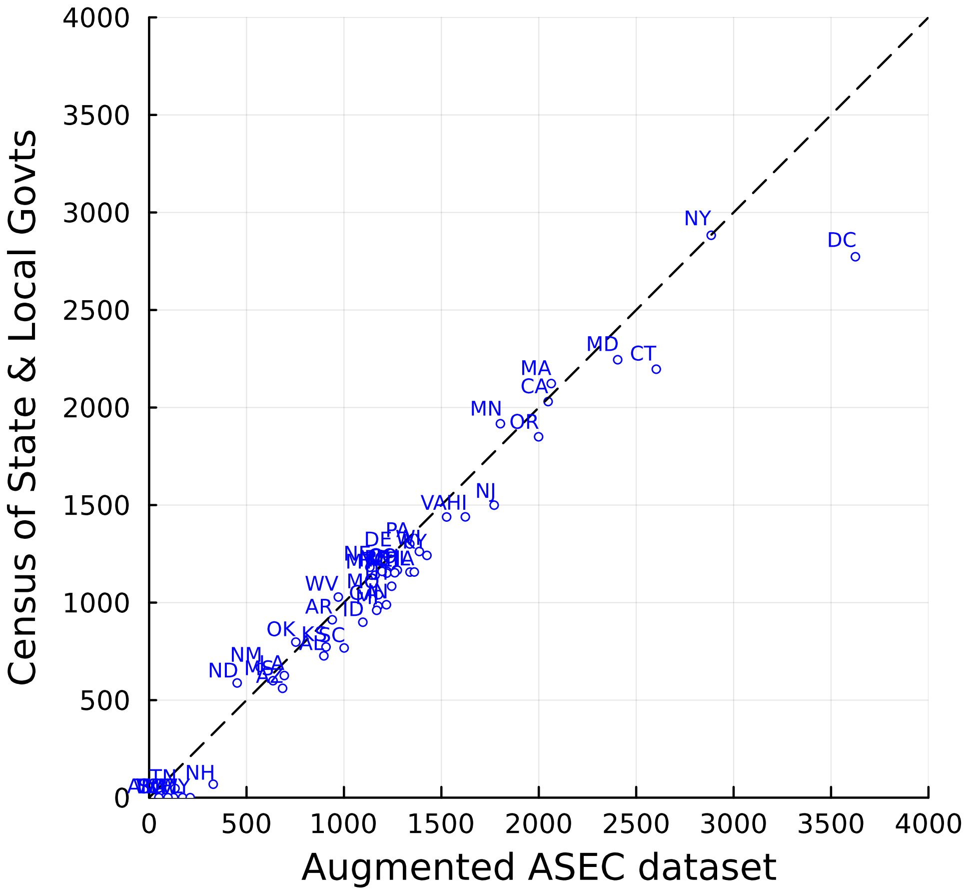

Figure G1: Per capita state and local income tax collections in current $, in the augmented ASEC dataset (horizontal axis) and the CSLG (vertical axis) for 2015 and 2016. Computed using ASEC household weights.

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

Property Taxes Figure G2 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 & Young (2016) on commercial property taxes collections to construct a measure for property taxes collected from households only. As the numbers of Ernst & 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 (for example, Wyoming) and in states with especially large per capita property taxes (Connecticut, New Hampshire). This result indicates that our estimates of property tax regressivity are lower bounds in those states.

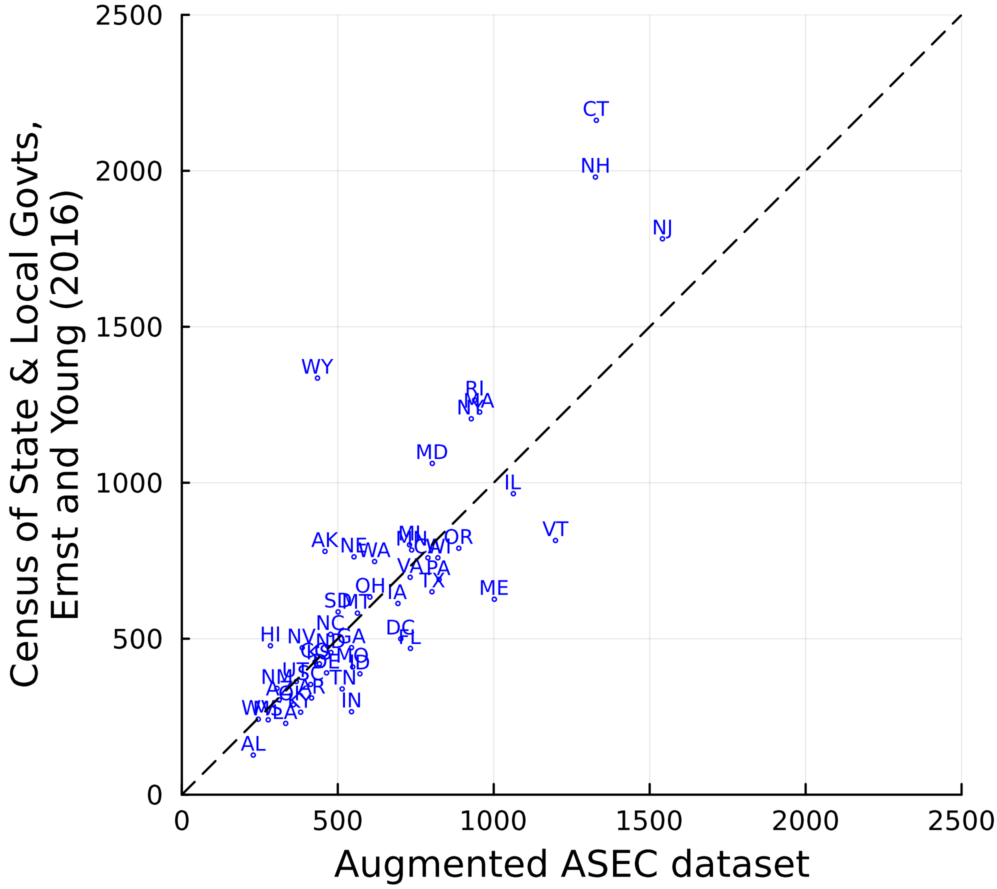

Figure G2: Per capita state and local household property tax collections in current $, in the augmented ASEC dataset (horizontal axis) and the CSLG (vertical axis) for 2015 and 2016. Computed using ASEC household weights. Commercial property tax collections have been excluded using the data provided by Ernst & Young (2016).

Consumption Taxes We impute sales and excise taxes for all ASEC households as described in Appendix E. Figure G3 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 & Young (2016) to construct a measure for taxes paid by households only.

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

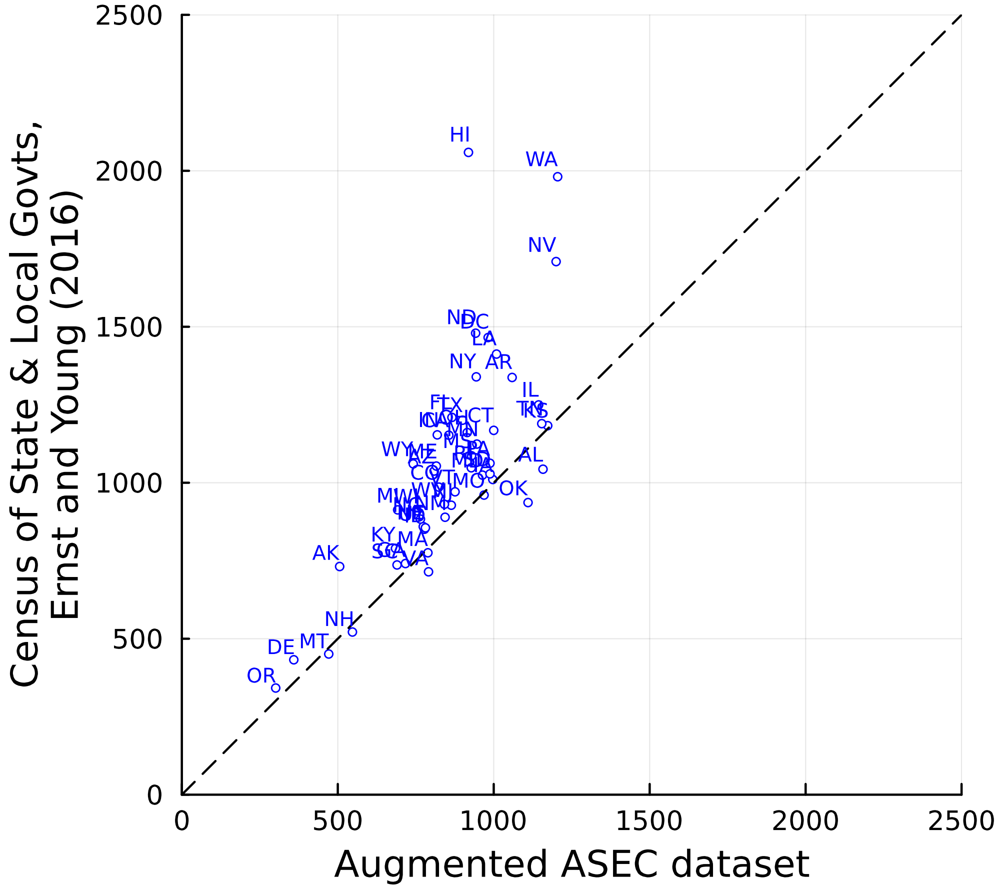

Figure G3: Per capita state and local consumption tax collections in current $, in the augmented ASEC dataset (horizontal axis) and the CSLG (vertical axis) for 2015 and 2016. Computed using ASEC household weights. Business tax collections have been excluded using the data provided by Ernst & Young (2016) and as explained in Section E.

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 & Young (2016) underestimating sales and excise taxes paid by businesses. For example, Ernst & Young (2016) imputes that businesses in Hawaii pay about 40 percent of general sales taxes, which is the same level as they impute for the nation as a whole. However, unlike businesses in 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: the Supplemental Nutrition Assistance Program (SNAP, ”Food Stamps”), Temporary Assistance for Needy Families (TANF), Housing Assistance, Alaska Permanent Fund Dividends (APFD), Medicaid, and Medicare.

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."[81]

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.[82] 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).[83] 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 differs substantially, because per capita AFDC spending varied greatly among states.[84] 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.[85] 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,

[81] According to Center on Budget and Policy Priorities (2022), this 50 percent administrative cost share are equivalent to about 5 percent of total SNAP spending.

[82] See Hoynes and Ziliak (2018) for details on spatial heterogeneity in the purchasing power of SNAP benefits.

[83] Ziliak (2015) provides a comprehensive description of the TANF program.

[84] See Moehling (2007) for a lucid summary on the evolution of state welfare systems.

[85] This maintenance of effort (MOE) requirement is about 75 percent of AFDC spending.

Pratt, and Okoli (2017) document this feature of TANF in detail. Second, there is large 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 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.”

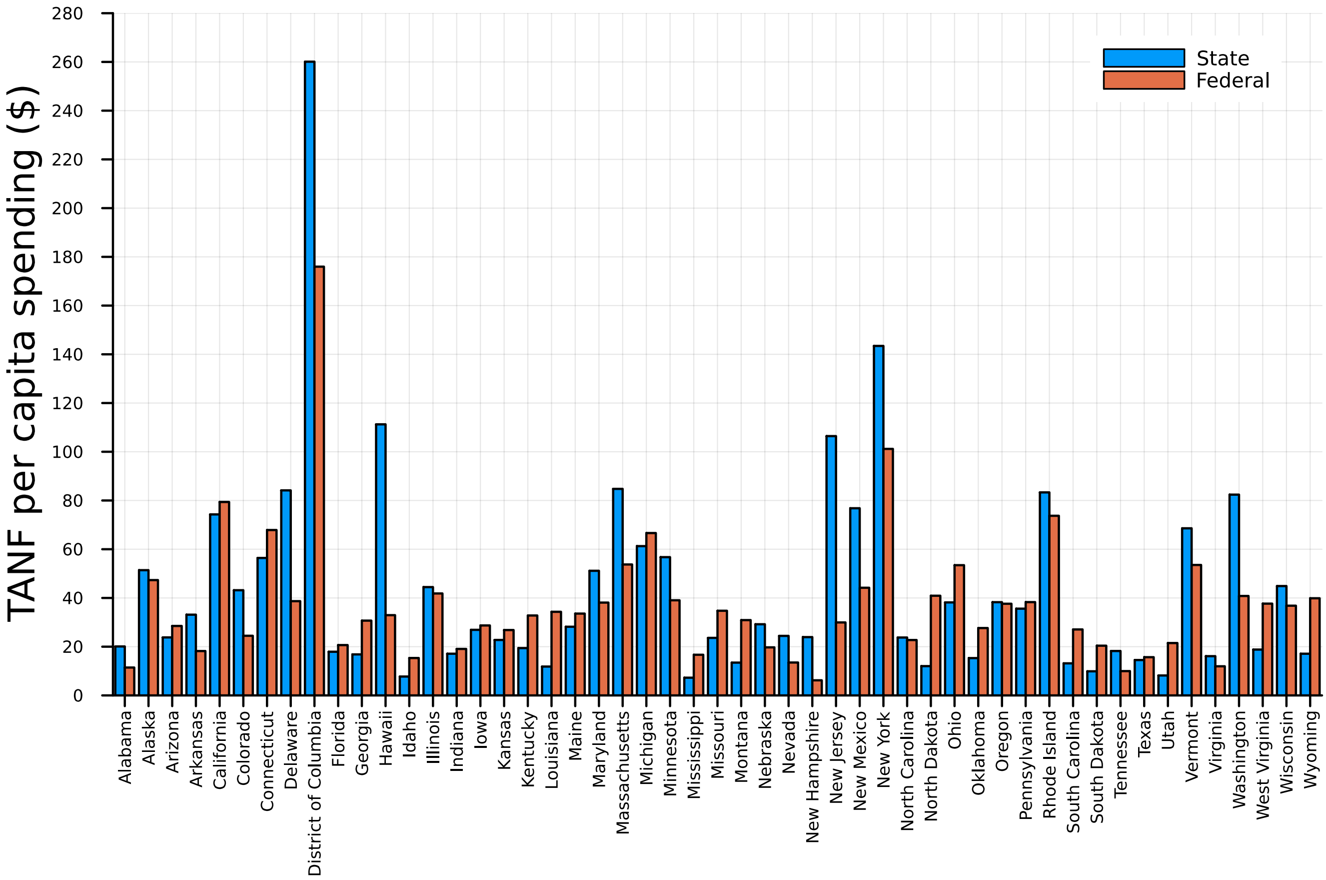

Figure H1: Federal and state per capita TANF spending in 2016. Computed from TANF financial data provided by the Office of Family Assistance (OFA).

For 2016, Figure H1 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 IPUMS variable INCWELFR.[86] To split the reported numbers into federal and state components, we use program data from the Office of Family Assistance (OFA).[87]

[86]The ASEC questionnaire asks to report ”cash assistance” for this variable, so it might include other state and local cash transfers received.

[87]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 percent (83 percent) in West Virginia to 71 percent (29 percent) in Washington with a national mean of 42 percent (58 percent).

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. For illustration, Pelletiere, Canizio, Hargrave, and Crowley (2008) estimate that in 2008, across all states, state spending on housing assistance amounted to $1.7bn, compared with the nearly $30bn spent on the three major federal housing assistance programs (public housing, Section 8 project based housing, and Section 8 vouchers).[88] To measure the household transfers provided by federal housing assistance support, we use the respective variable imputed into the ASEC dataset by the CBO.[89]

H.4 Alaska Permanent Fund Dividends (APFD)

Using data from the Alaska Permanent Fund Corporation, Berman and Reamey (2016) report that more than 90 percent of Alaska residents receive Alaska Permanent Fund Dividends (APFD) every year. Those dividends vary by year but are typically around $1,200 per capita.[90] 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."[91] 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 percent 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 expen-

[88] 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.

[89] See https://github.com/US-CBO/means_tested_transfer_imputations

[90] For example, for the years 2015 and 2016, they amounted to per capita payments of $2,072 and $1,022, respectively.

[91] Indeed, in our sample, the mean of this variable in Alaska is ten to twelve times larger than in other states.

ditures in 2016 totalled $583bn (equivalent to 3.1 percent of GDP) and represented about 17.4 percent of total national health expenditures.[92] As of December 2016, the programs covered about 75 million beneficiaries (one in five Americans), making it the by far largest means-tested transfer program in the US, with respect to both 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 percent and enrollment by more than 55 percent.[93]

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 income is below a certain percentage of the Federal Poverty Level, 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.[94] 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 percent in Vermont to 96 percent in Nevada. Cross-state differences in eligibility and enrollment increased even further after the Affordable Care Act (ACA, or "Obamacare") took effect in 2014 as it allowed states to expand eligibility to non-elderly adults with incomes up to 133 percent 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 H2.

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.[95] 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, which can be summarized as "each state's Medicaid benefits package is unique" (Schneider and Garfield, 2002).

[92]The other sizable payers were Medicare (20.1 percent) and private insurance (34 percent).

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

[94]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.

[95]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.

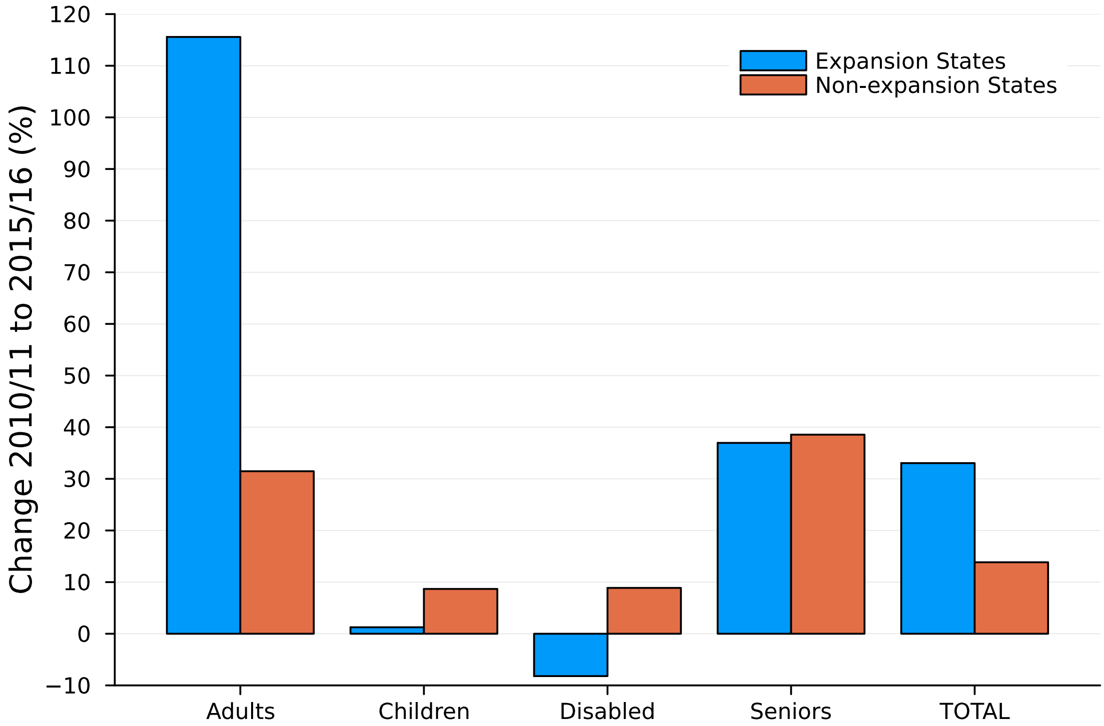

Figure H2: Change in Medicaid Enrollment by State between 2010/11 and 2015/16. Changes are computed using data provided by the Centers for Medicare & Medicaid Services (CMS), the Kaiser Family Foundation, and the Medicaid and CHIP Payment and Access Commission (MACPAC).

To summarize the effect of Medicaid and CHIP's mandatory and optional parameters, Figure H3 shows average spending per recipient (left) for 2016 and the share of each state's population that 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 percent of the state populations of Idaho, Kansas, Nebraska, North Dakota, South Dakota, Utah, Virginia and Wyoming, and above 30 percent in Arkansas, DC, Kentucky, Louisiana, New Mexcio, New York, Vermont and West Virginia.

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 percent, 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. The reason is that recipients neither receive bills nor are required to pay out of pocket.

The Congressional Budget Office (CBO) has developed an algorithm that 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), its 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

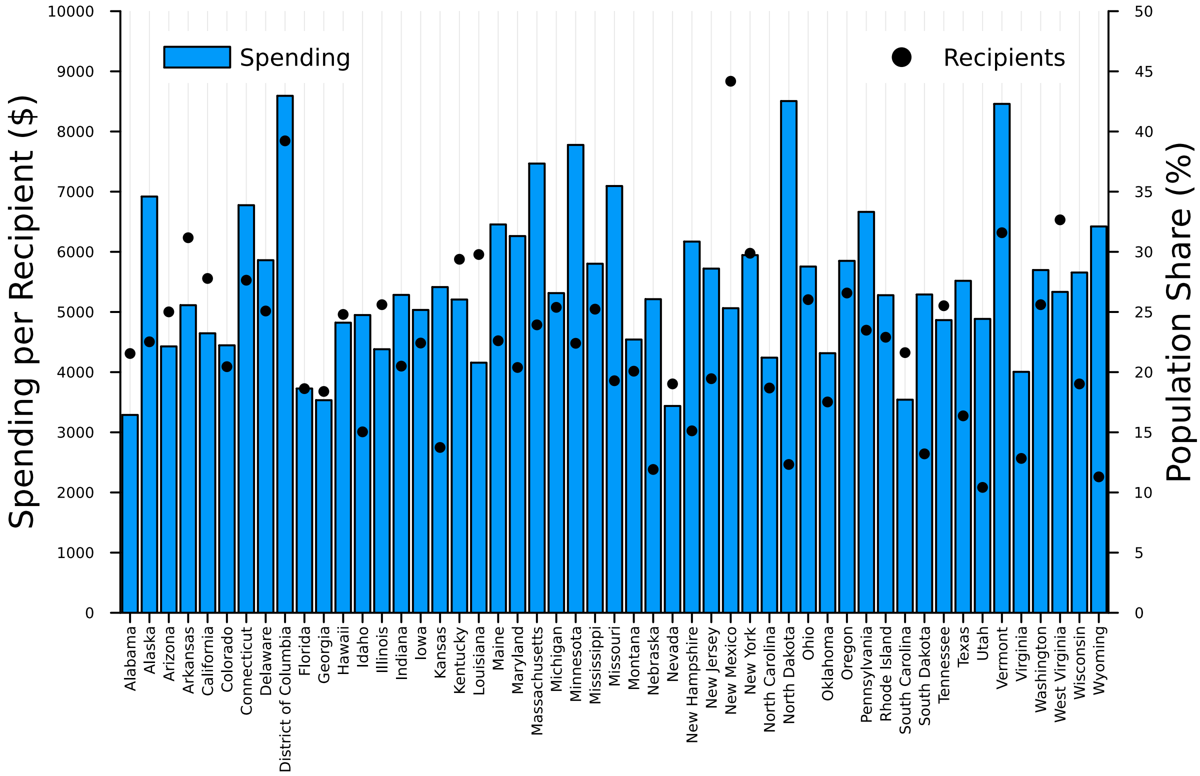

Figure H3: Medicaid spending per recipient (left axis) and Medicaid recipients as share of state population (right axis), 2016. Recipients include part-year recipients. Source: Centers for Medicare & Medicaid Services (CMS), Kaiser Family Foundation, Medicaid and CHIP Payment and Access Commission (MACPAC).

heterogeneity within enrollment groups to capture differences in within-year coverage periods.[96]

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 adjust the CBO's algorithm by (i) targeting state-level enrollment numbers, and (ii) using state average spending for each enrollment group.[97]

Another adjustment we make is that we consider only 40 percent of the imputed administrative spending as a person-level transfer, and refer to this as the Medicaid and CHIP ”cash value.” This 40 percent share is based on Finkelstein, Hendren, and Luttmer (2019), who argue that the remaining 60 percent of Medicaid spending effectively benefits agents other than Medicaid enrollees, including hospitals, which, without 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 percent 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 percent of total spending; the share

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

[97] 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.

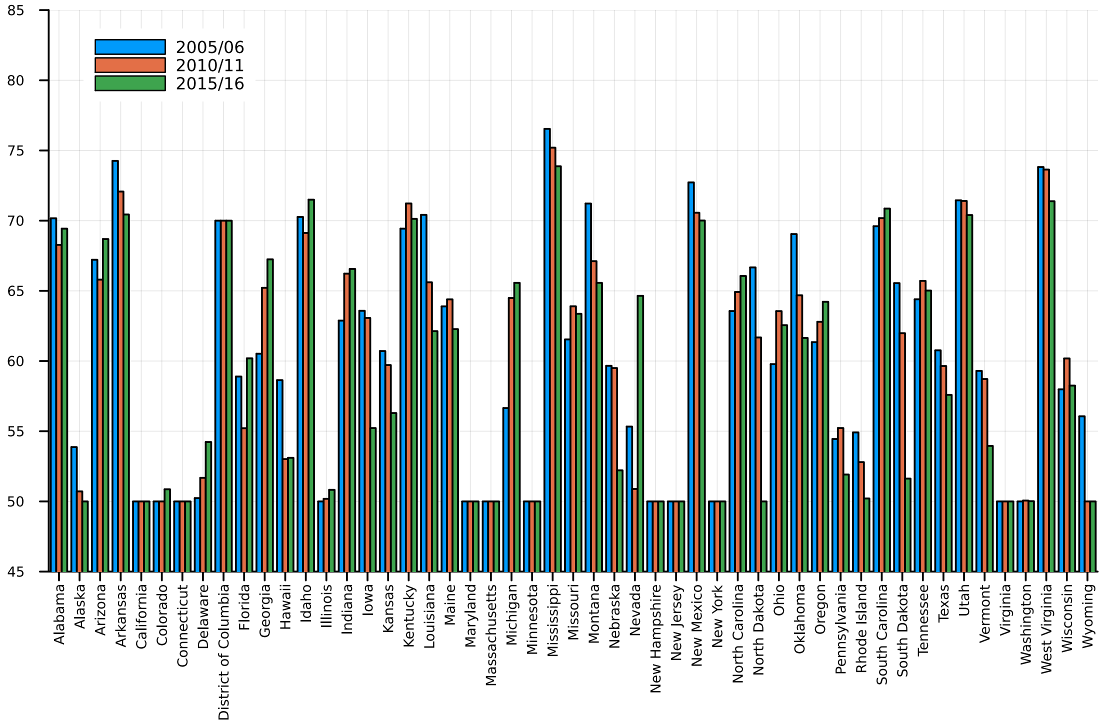

Figure H4: Federal Medicaid Assistance Percentages (FMAPs), averages of adjacent years. Source: Federal Register.

for CHIP was 82 percent.[98] 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:

$$FMAP_{s,t} = \min\left\{ \max\left\{0.83, 1 - \frac{(y_{s,t})^2}{(y_{US,t})^2} \times 0.45\right\}, 0.5\right\}, \tag{H1}$$

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 percent or less than 50 percent). Figure H4 shows FMAPs for every state in our sample years.[99]

The National Association of State Budget Officers (2017) documents that states dedicated, on average, 28.7 percent of their total expenditure to Medicaid in 2016. However, because of different FMAPs and differences in state-level Medicaid eligibility and generosity options, spending ranged from 11.4 percent in Wyoming to 37.7 percent 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).[100]

[98] 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.

[99] As mentioned by Buchmueller, Ham, and Shore-Sheppard (2015), DC's FMAP has been set at 70 percent 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.

[100] 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.

H.6 Medicare

Medicare is a federal program that 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 because of regional differences in cost and utilization.[101]

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.[102] 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" (CMS).[103]

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 H5.

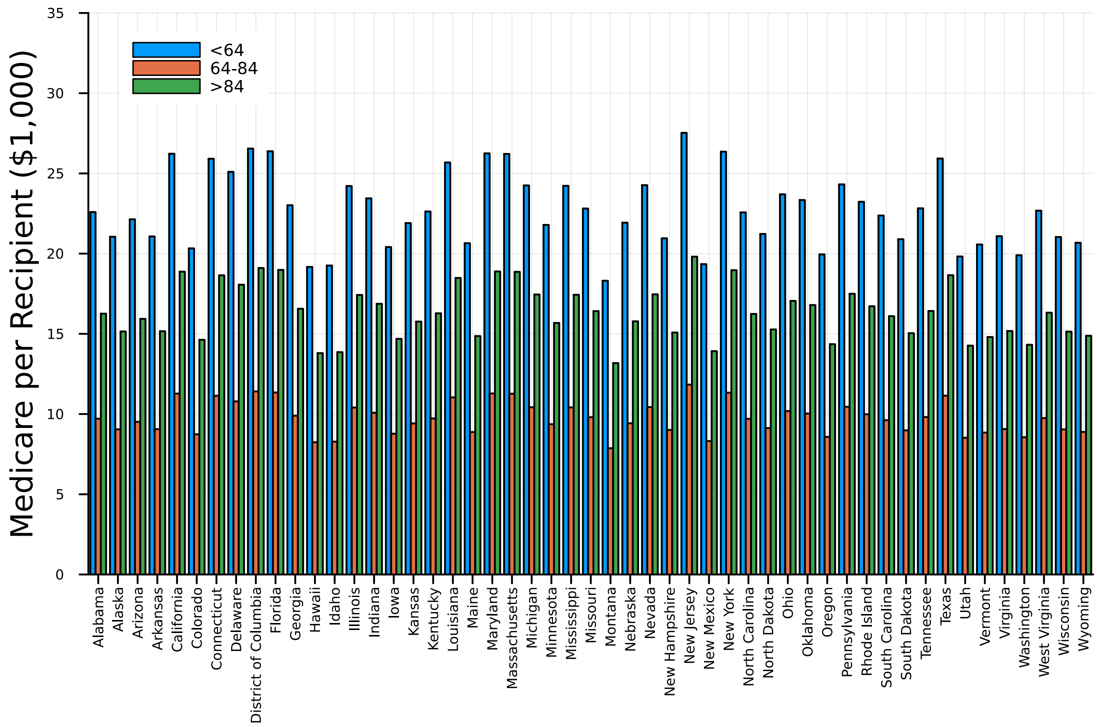

Figure H5: Average Medicare per Enrollee Spending in 2016 for three different age groups. Source: Centers for Medicare & Medicaid Services and authors' computations.

Finally, to convert the public spending amounts into household cash values, we use an estimate from Finkelstein

[101]According to Super (2003), spending in one state can be about 50 percent of spending in another state. As noted by Centers for Medicare & Medicaid Services (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."

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

[103]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.

and McKnight (2008), who found that eligibility for Medicare reduced the sum 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 percent 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 original ASEC weights, w_i, and compute the weight share of each decile W_j with $j = 1, ..., 10$:

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

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:

$$\begin{aligned} W_{1,s} &= \frac{\sum_i I_{\{y_i \leq Y_1 \text{ and } i \in s\}} w_i}{\sum_i w_i} \\ W_{2,s} &= \frac{\sum_i I_{\{y_i > Y_1 \text{ and } y_i \leq Y_2 \text{ and } i \in s\}} w_i}{\sum_i w_i} \\ &\ldots \end{aligned}$$

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

$$w_i^{new} = \frac{W_1}{W_{1,s}} w_i,$$

and proceed analogously for households with different incomes.

Note that

$$\begin{aligned} \sum_i I_{\{y_i \leq Y_1 \text{ and } i \in s\}} w_i^{new} &= \frac{W_1}{W_{1,s}} \sum_i I_{\{y_i \leq Y_1 \text{ and } i \in s\}} w_i \\ &= \frac{W_1}{W_{1,s}} W_{1,s} \sum_i I_{i \in s} w_i, \\ &= W_1 \sum_i I_{i \in s} w_i, \end{aligned}$$

and thus

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

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

Figure I1 illustrates the effect of this reweighting procedure on state income distributions. Using the new weights aligns them closely to the national distribution.

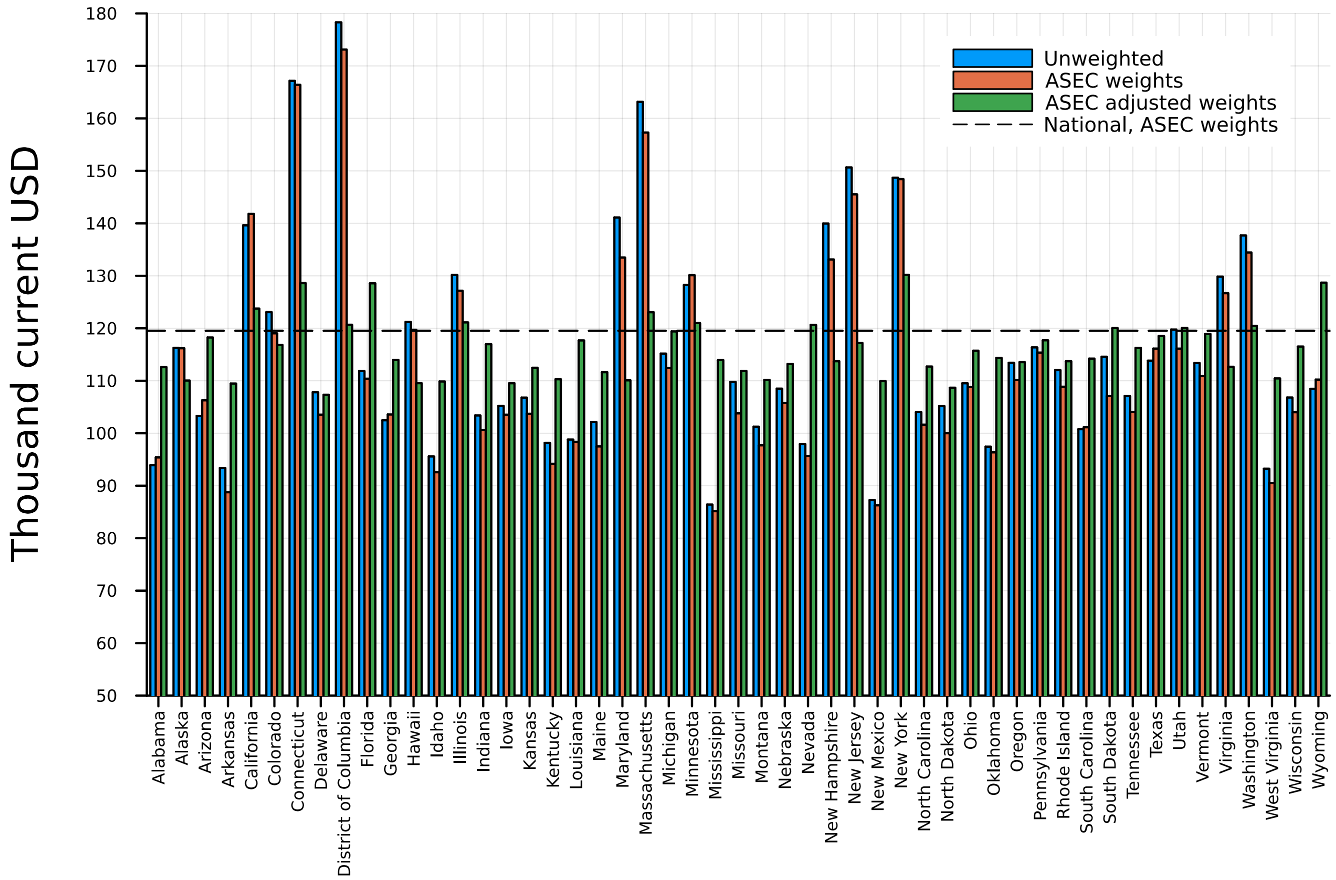

Figure I1: Means of ASEC sample household income distributions using different (no) weights (2015/2016).

J More Results on Baseline State Progressivity

This section contains additional results for the state tax and transfer progressivity estimates presented in Section 4.

J.1 Differences in the Cross-Section

Figure J1 plots the contributions to overall state progressivity shown in Figure 17 separately for each tax and compares them with the (unweighted) state average. The figure illustrates that state income taxes are progressive, while all other taxes are regressive. The regressivity of sales and excise taxes is similar in all states, but the regressivity of property taxes varies substantially and is especially strong in states with high property tax rates, like New Hampshire, New

Jersey, Vermont and Connecticut. The figure also illustrates that states with no income taxes do not have other taxes that are less regressive than those in other states. Hence, income taxes play an important role in determining *relative* overall state progressivity.

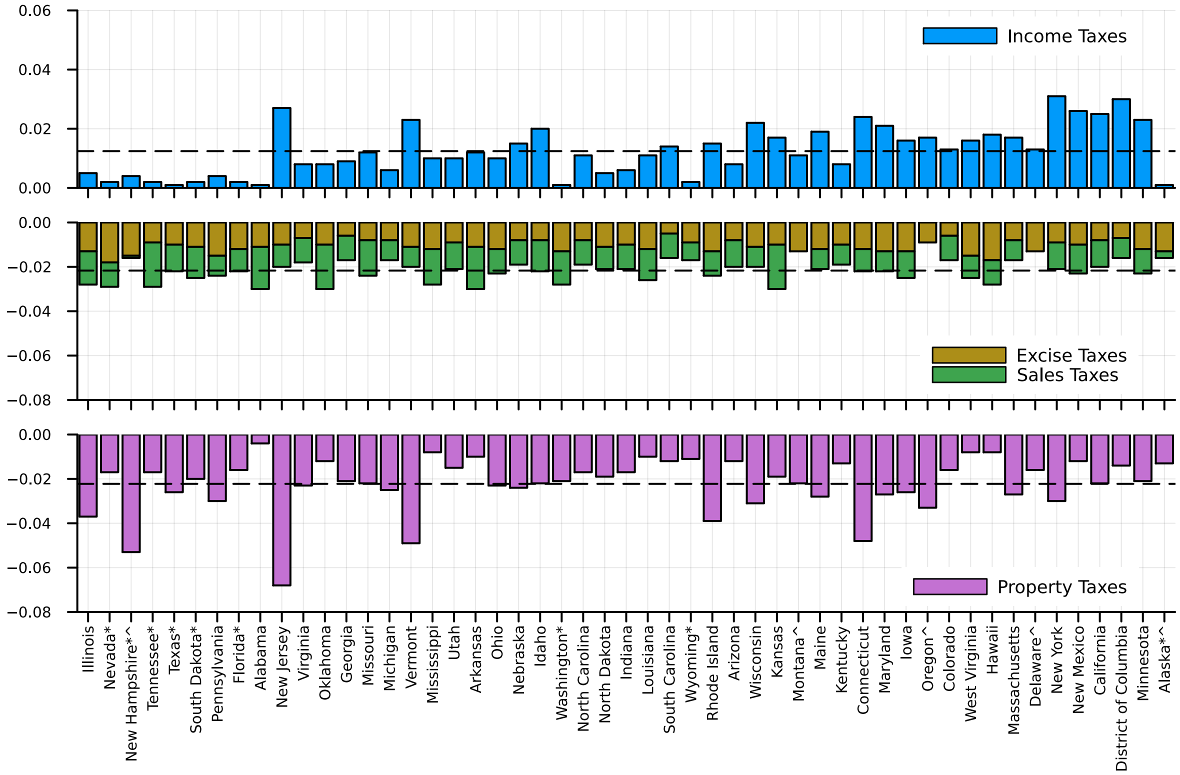

Figure J1: State level contributions to state progressivity, τ_s, (or regressivity if negative) from income, sales and excise and property taxes. Horizontal dashed lines are unweighted state averages. Estimates are for 2015/2016. See notes to Figure 17.

Figure J2 plots the geographic distribution of our overall state progressivity estimates shown in Figure 17 (as black dots). Darker shading indicates more progressive state taxes and transfers. Regressive states are concentrated in the South, while states in the West, Midwest and Northeast tend to have more progressive taxes and transfers.

J.2 Differences over Time

Table J1 reports average state progressivity estimates and the standard deviation of those estimates across states for our three sample periods. The first row, labeled "Baseline," corresponds to the τ_s values discussed in Section 4.3. 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 shows that Medicaid pushed up both average state progressivity and its dispersion between 2010/11 and 2015/16.

Figure J3 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

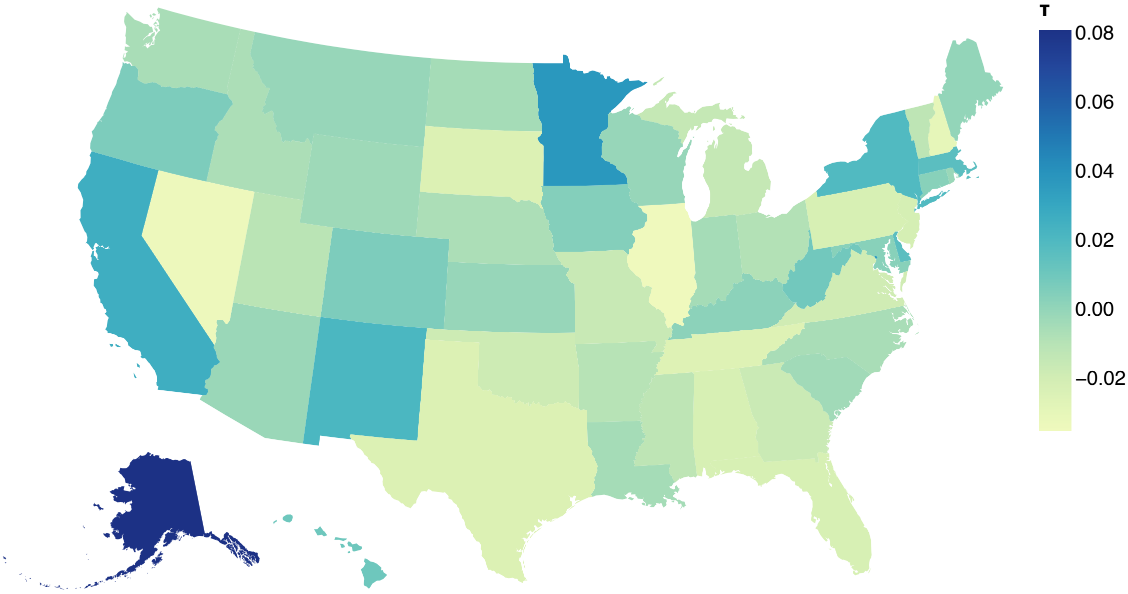

Figure J2: Overall state-level progressivity estimates, τ_s, as reported in section 4.3. Estimates refer to 2015/2016. See notes to Figure 17.

	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 J1: Estimates of state tax and transfer progressivity. ”Baseline” refers to τ_s (see Section 4.3). State estimates are unweighted. 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.

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.

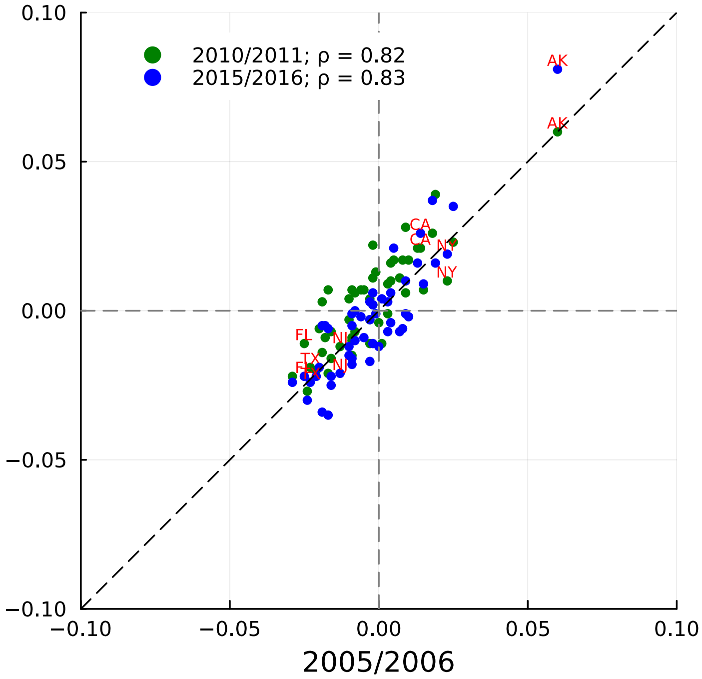

Figure J3: Time Variation in State Progressivity, τ_s. Estimate uses all state taxes and transfers (see Section 4.3); ρ is the Spearman's rank correlation coefficient for 2005/2006-2010/2011 and 2005/2006-2015/2016.

K 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 percent. 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). On the basis of these findings, in what follows, we assume that the labor share of the tax incidence is 40 percent, the midpoint of these various estimates.

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

K.1 Federal Corporate Income Taxes

Operationally, let T_t^{corp} be the total federal corporate tax revenues in year t, W_t be the total wage bill, and $Wshare_t(q)$ 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

$$t_{q=100,t}^{corp-lab} = \frac{0.4 \times 0.6 \times T_t}{W_t \times Wshare_t(100)},$$

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

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

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 $Dshare_t(q)$ 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

$$t_{q,t}^{corp-div} = \frac{0.6 \times T_t}{D_t \times Dshare_t(q)}.$$

K.2 State Corporate Income Taxes

We assume that the 60% 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.

We also assume that the residual 40% pass-through from state corporate taxes on labor income is local; i.e., it falls entirely on workers of that state.[104] We allocate this component across workers exactly as done for federal taxes. The approach is thus 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.[105]

[104] Put differently, large multi-establishment 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 establishments located in other states.

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

K.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[106], 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).[107]

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.

L 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 business 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 & 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 exclude 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 realized 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 two-thirds of public utility taxes and all insurance taxes, we subtract these amounts to avoid double counting. We also subtract amusement taxes and assume they are all paid by households, so we include them

[106] See here: https://obamawhitehouse.archives.gov/omb/budget/Historicals.
[107] Note that dividend income is self-reported in ASEC, while ordinary dividend income is a separate line item in the IRS-SOI tables.

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 paid on purchases of inputs, and (2) *property taxes*, which include only the property tax on commercial real estate owned by the business.

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 Bureau of Economic Analysis (BEA)[108] with the categorization proposed by Delgado, Bryden, and Zyontz (2014), which splits industries according to 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.[109]

Thus, the effective tax rate on local labor is

$$t^{m_L}_{s,t} = \frac{\alpha^{tr}_{s,t}R^m_{s,t}}{Y^L_{s,t}}. \tag{L1}$$

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

Businesses that 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.[110]

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

$$t^{m_C}_{s,t} = \frac{(1-\alpha^{tr}_{s,t})R^m_{s,t}}{C^{ntr}_{s,t}}. \tag{L2}$$

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

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

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

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

in our dataset.

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 & 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.[111] Let $Y^B_{s,t}$ be total business income in state s and year t, estimated from BEA data.[112]

The effective property tax rate that falls on business owners is

$$t^{h_B}_{s,t} = \frac{\alpha^{land}_{s,t} \hat{R}^h_{s,t}}{Y^B_{s,t}}. \tag{L3}$$

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 like 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,

$$t^{h_L}_{s,t} = \frac{\alpha^{tr}_{s,t} \left(1 - \alpha^{land}_{s,t}\right) \hat{R}^h_{s,t}}{Y^L_{s,t}}, \tag{L4}$$

and

$$t^{h_C}_{s,t} = \frac{\left(1 - \alpha^{tr}_{s,t}\right) \left(1 - \alpha^{land}_{s,t}\right) \hat{R}^h_{s,t}}{C^{ntr}_{s,t}}. \tag{L5}$$

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 L1 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).

[111] 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 that is consistent between the ASEC and SOI data, we sum ASEC business and farm income, as Larrimore, Mortenson, and Splinter (2021) show that those two variables are similar to SOI business income.

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

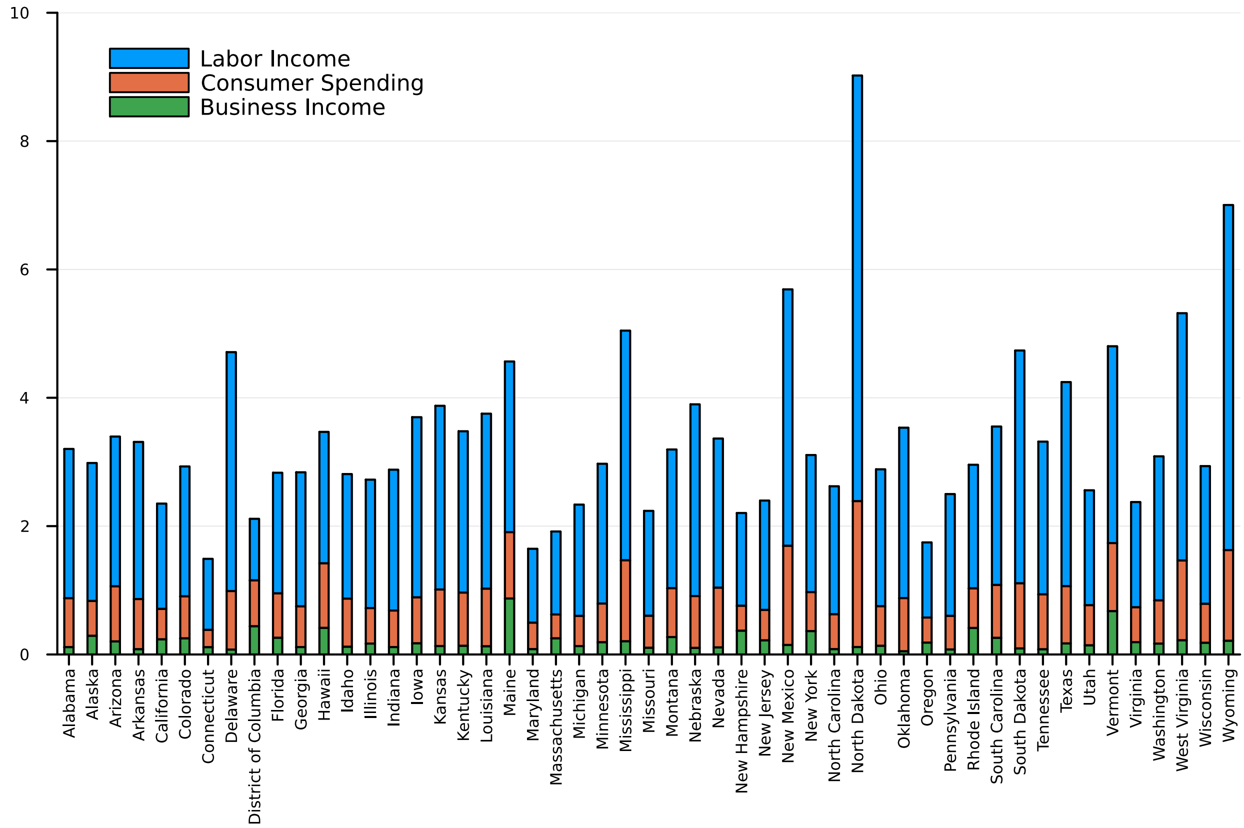

Figure L1: Effective business tax rates by state (2015/2016). Computed by dividing total state household gross income by total taxes paid using the entire augmented ASEC dataset and household weights.

M Public Spending as a Transfer

M.1 Federal Spending

We obtain data on federal spending from NIPA Table 3.16, Government Current Expenditures by Function for 2005/2006, 2010/2011, and 2015/2016. In our measure of spending, we include general public service (line 43 of Table 3.16), 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). We exclude income security (e.g., unemployment insurance and other welfare and social insurance benefits) and health (e.g., Medicare) because they are already part of our transfer calculations. All spending is allocated as a transfer per capita, and then per household, according to the number of household members. The only exception is elementary and secondary education spending (a component of education), which is allocated proportional to the number of school-age children in the household.

M.2 State and Local Spending

We obtain data on state and local spending from the Census of State and Local Governments dataset of the Census Bureau for years 2005/2006, 2010/2011, and 2015/2016. Unless noted otherwise, the allocation of state and local spending as a transfer is also per capita. We include a subset of the available expenditures in our calculations:

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 already noted in the main text, and in line with federal spending on the same item, elementary and secondary education net of charges for school lunches are assigned to households based on the number of school-age children in the household.

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), and 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), and 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), and 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), and 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), and 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 M1 shows this measure of state and local spending on public goods and services scaled per state resident for our sample years.

N Extensions: Additional Results

In this section, we break down the contributions of the additional taxes and transfers considered in Section 5 on state average net tax rates and state progressivity. To facilitate understanding of how these extensions change our baseline estimates, we retain the ranking of states implied by the baseline tax rate and progressivity estimates in all plots.

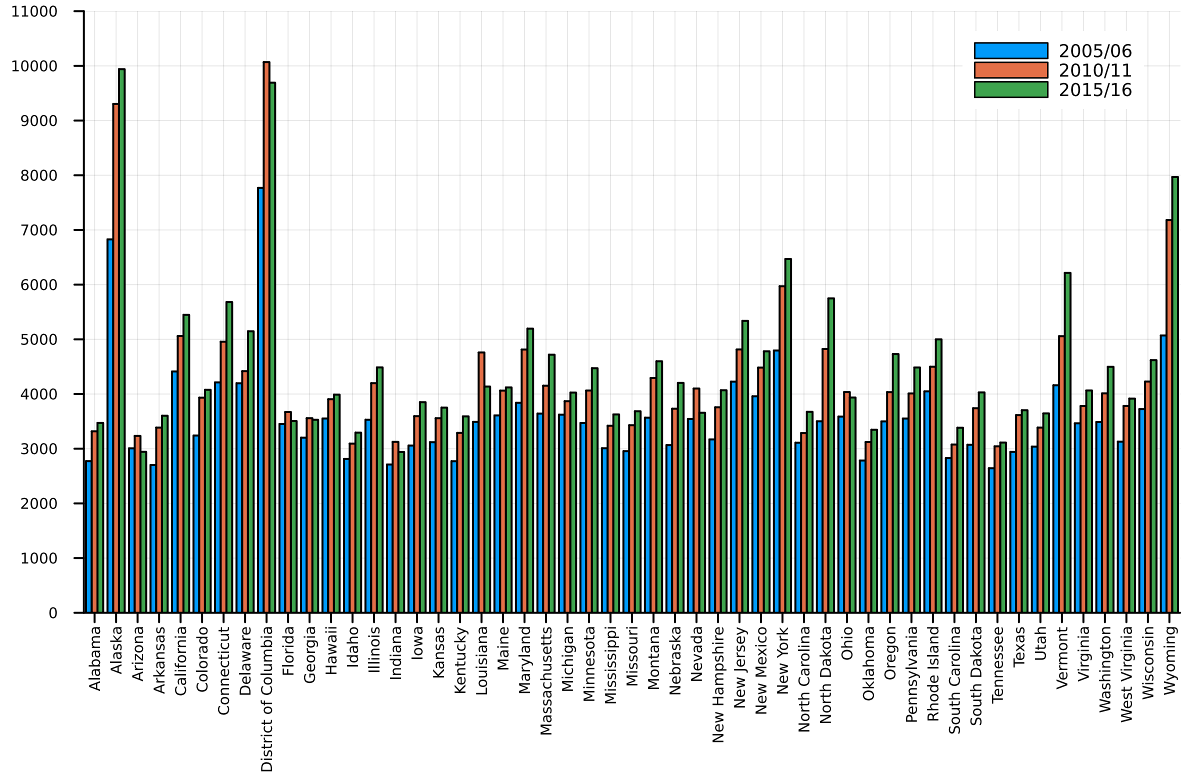

Figure M1: State and local spending on public goods and services per state resident, in current $. Computed from the augmented ASEC dataset using household weights. Population data are from the Census Bureau.

N.1 Corporate Income and Business Taxes

Figure N1 adds corporate income and business taxes to the average tax and transfer rates shown in Figure 14. 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 percent, respectively). Second, the increases are larger in states that previously had lower net tax rates, especially in those states without income taxes—for example, Wyoming and Texas. This result indicates 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 0.71.

As shown in the ”Extension 1” panel of Table 4, including federal corporate income taxes increases progressivity, which reflects 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 that are mildly regressive in aggregate (the progressivity estimate drops from -0.004 to -0.011). Including all federal and state corporate and business taxes raises federal and state aggregate progressivity from 0.202 to 0.227, which the large positive contribution to progressivity from the federal corporate income tax.

Next, 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 state taxes (and transfers). Figure N2 adds to the earlier decomposition corporate income and business taxes. In all states, corporate income taxes are progressive, but the magnitude of

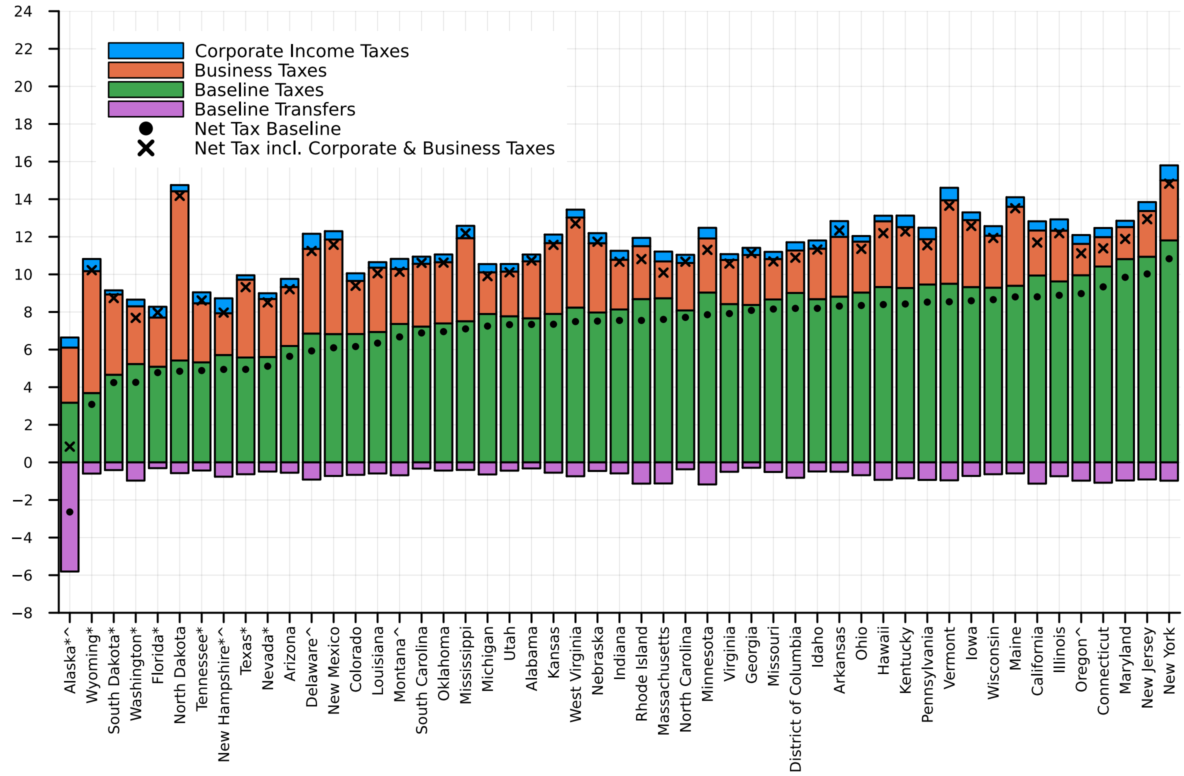

Figure N1: Average tax and transfer rates by state. Baseline taxes includes income, excise, sales and property taxes. Baseline sample, 2015/2016. See notes to Figure 14.

their contribution to overall progressivity is small. Business taxes, on the other hand, are regressive in all states, and their contribution differs substantially across states. Business tax regressivity is especially large in Vermont, North Dakota, Wyoming and New Mexico.

In general, states whose tax systems are regressive without corporate and business taxes appear even more regressive when these taxes are included. The Spearman's rank correlation coefficient between the rankings implied by the two different progressivity measures is 0.96.

N.2 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 percent of spending for Medicare and 40 percent 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 N3.

Figure N4 shows average state tax and transfer rates by state once we include Medicaid valued at the amount spent. In this figure, we include only the state portion of the extra Medicaid portion, while Figure N3 shows both the state and federal portions. On average, the extra Medicaid doubles the total transfer rate (except in Alaska) but it lowers the net rate only by about 1.5 percentage points. Relative to our baseline, this alternative assumption does not have much impact on the cross state ranking of net tax rates. (The rank correlation is 0.97.)

Figure N5 does the same thing for state tax progressivity. It shows that including the extra Medicaid transfer values

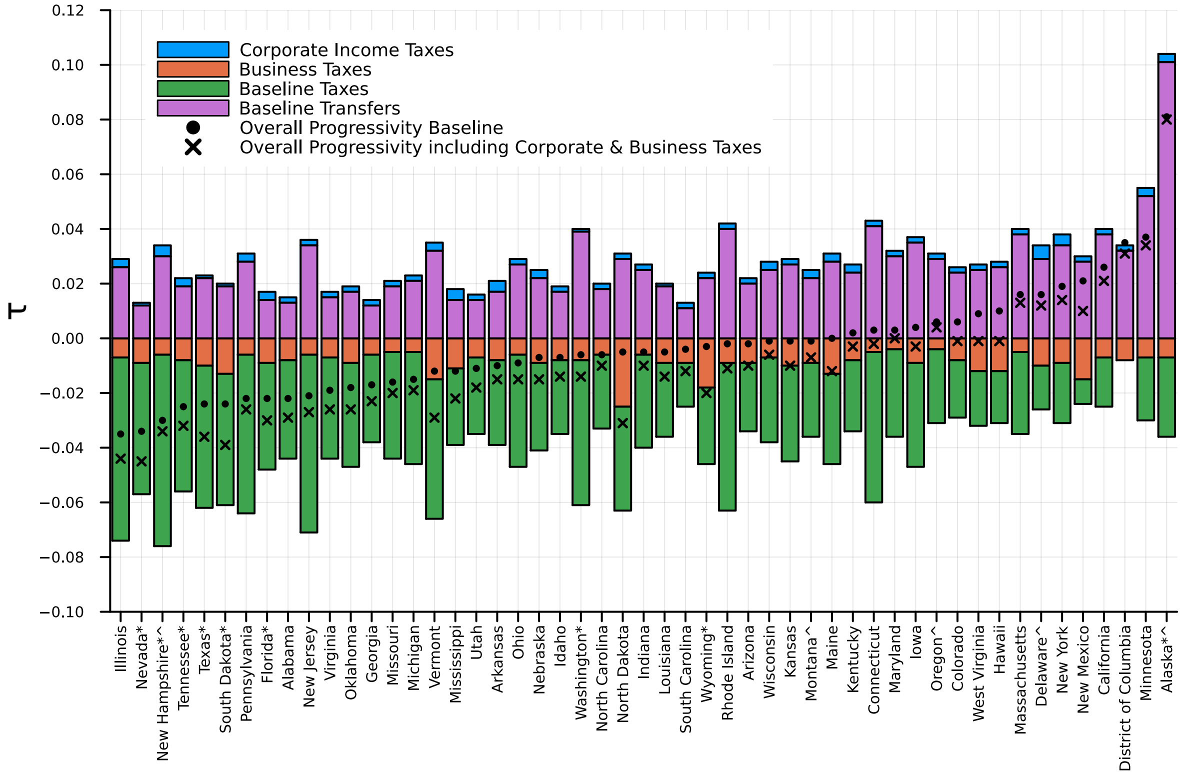

Figure N2: State progressivity decomposition. The plot shows estimates for progressivity induced by each of the state level taxes and transfers indicated in the legend, considering one at a time. Baseline taxes and baseline transfers are as in Section 4.3. See notes to Figure 17.

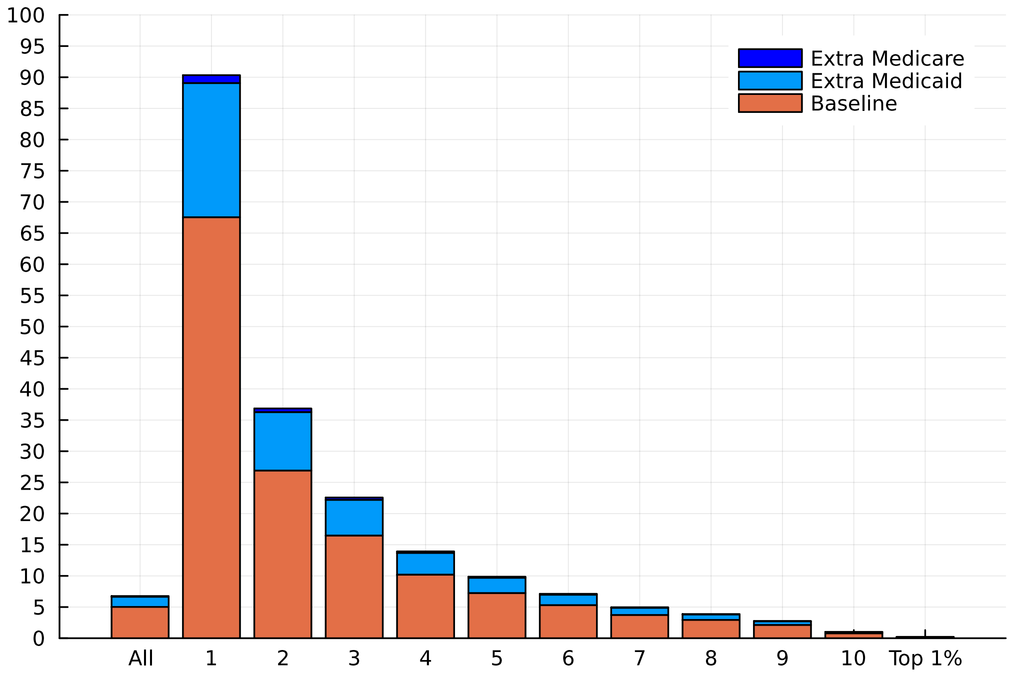

Figure N3: Average 2015/2016 transfer rates with Medicare and Medicaid at full cost. ”Baseline” includes all federal, state and joint transfer programs shown in table 2, with Medicaid and Medicare at 40 and 82 percent of administrative spending. ”Extra Medicaid” is the additional 60 percent of Medicaid spending (federal and state), and ”Extra Medicare” is the additional 18 percent of Medicare spending (federal). See notes to Figure 1.

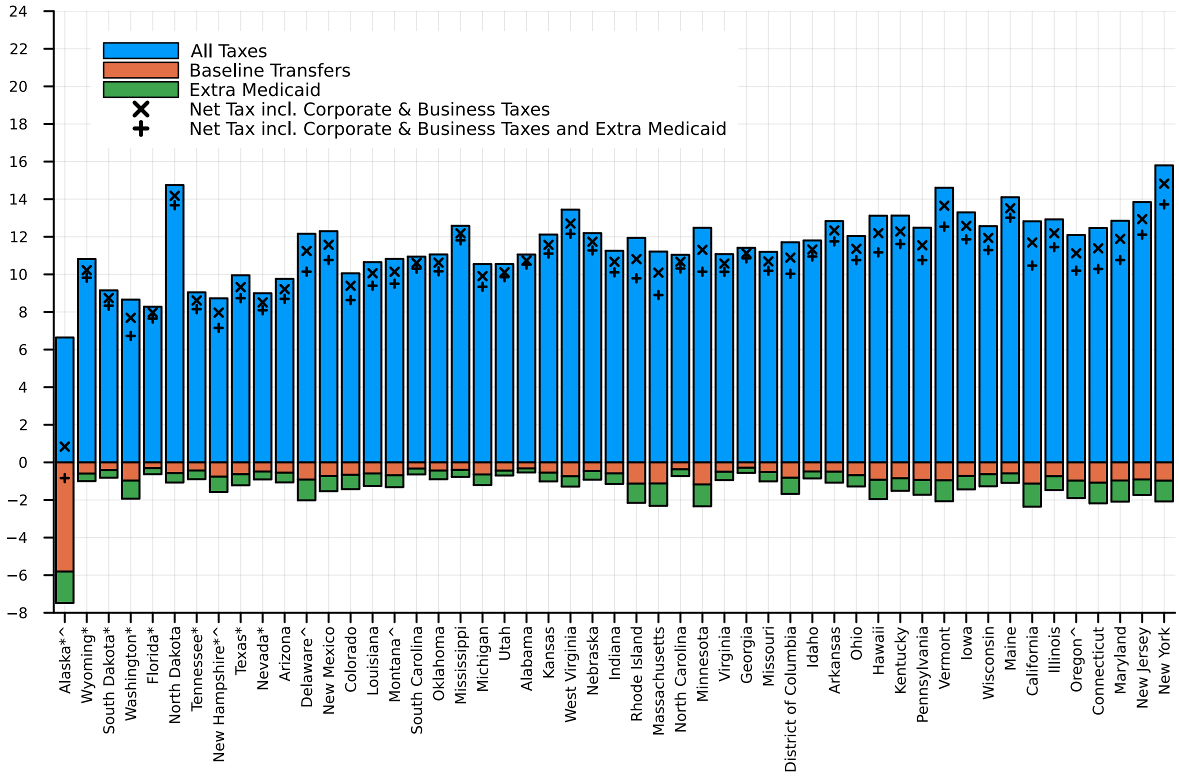

Figure N4: Average tax and transfer rates by state. "All Taxes" includes all baseline taxes (income, excise, sales and property taxes) as well as corporate income and business taxes. Baseline sample, 2015/2016. See notes to Figure 14.

has a sizable impact on overall state progressivity. As Medicaid is the largest of all transfers programs (see Table 3), adding the 60 percent value differential strongly increases progressivity in all states and turns τ_s positive in most states. By construction, the increase is strongest in states that already had large baseline transfer contributions to progressivity. Hence, adding the extra Medicaid transfers to the progressivity estimate – which includes the baseline taxes and transfers as well as corporate income and business taxes – does not change the state progressivity ranking much. The rank correlation coefficient is 0.91.

N.3 Federal, State and Local Spending

In this final extension, we consider federal and state spending on public goods and services a transfer to households and add it to baseline transfers and the extra Medicaid amount described in the previous section. We also retain the baseline taxes and the corporate income and business taxes described in Section N.1. Hence, the resulting progressivity measure is the most comprehensive we consider in this paper.

As shown by Figure 24 in Section 5.2, both federal and state spending are highly progressive, and the "Extension 2" panel of Table 4 illustrates that federal progressivity strongly increases (from 0.214 to 0.280) once the extra transfer value of Medicare and Medicaid, as well as federal spending, is included. The aggregate state tax and transfer system turns from regressive to progressive once this broad transfer measure is included. Recall that Medicare is a federal program, so it affects only progressivity estimates that include federal taxes and transfers. State spending, however, is sizable and drives up the state-taxes-and-transfers-only progressivity estimate. The aggregate federal and state progressivity estimate, which includes all baseline and extension taxes and transfers, is 0.372, which is almost double

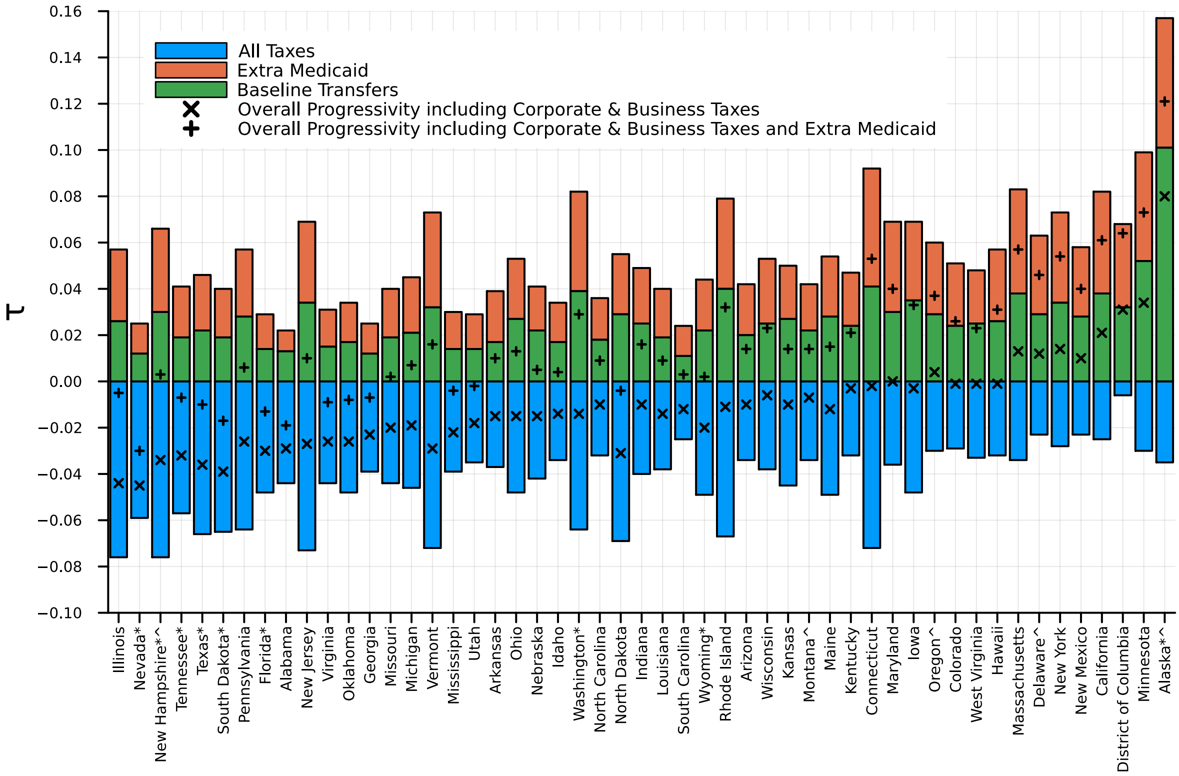

Figure N5: State progressivity decomposition. The plot shows estimates for progressivity induced by each of the state level taxes and transfers indicated in the legend, considering one at a time. Baseline transfers are as in Section 4.3. "All Taxes" is baseline taxes plus corporate income and business taxes. See notes to Figure 17.

our baseline progressivity estimate.

Figure N6 shows that once this broad measure of transfers is incorporated into our estimates, the average net tax rate across states (including Alaska) falls from about 10 percent to 2 percent and becomes negative in a few states. This is true mostly in states that have large state spending numbers per capita, such as Alaska, Wyoming and the District of Columbia, as shown by Figure M1 in Appendix M.2.

Finally, Figure N7 reports state-level estimates of overall progressivity under the extended tax and transfer measures, τ^*, and its decomposition. Under this broad measure of transfers, τ^* increases sharply, on average by 0.115, and becomes uniformly positive in all states. That is because spending on goods and services is large in all states, which translates into large values for this broad transfer measure. Because cross-state spending differences are relatively minor (Alaska, Wyoming and the District of Columbia are exceptions), the rank correlation of the two progressivity estimates remains large (0.82).

O Alternative Progressivity Estimates

We have estimated tax progressivity via a least squares regression of log household disposable income on log pre-government income. This power tax function does not perfectly capture net taxes actually paid household by household, for two reasons. First, taxes vary by income in a more complicated fashion than our simple two parameter function can replicate. Second, net taxes paid depend on a range of other characteristics besides household income,

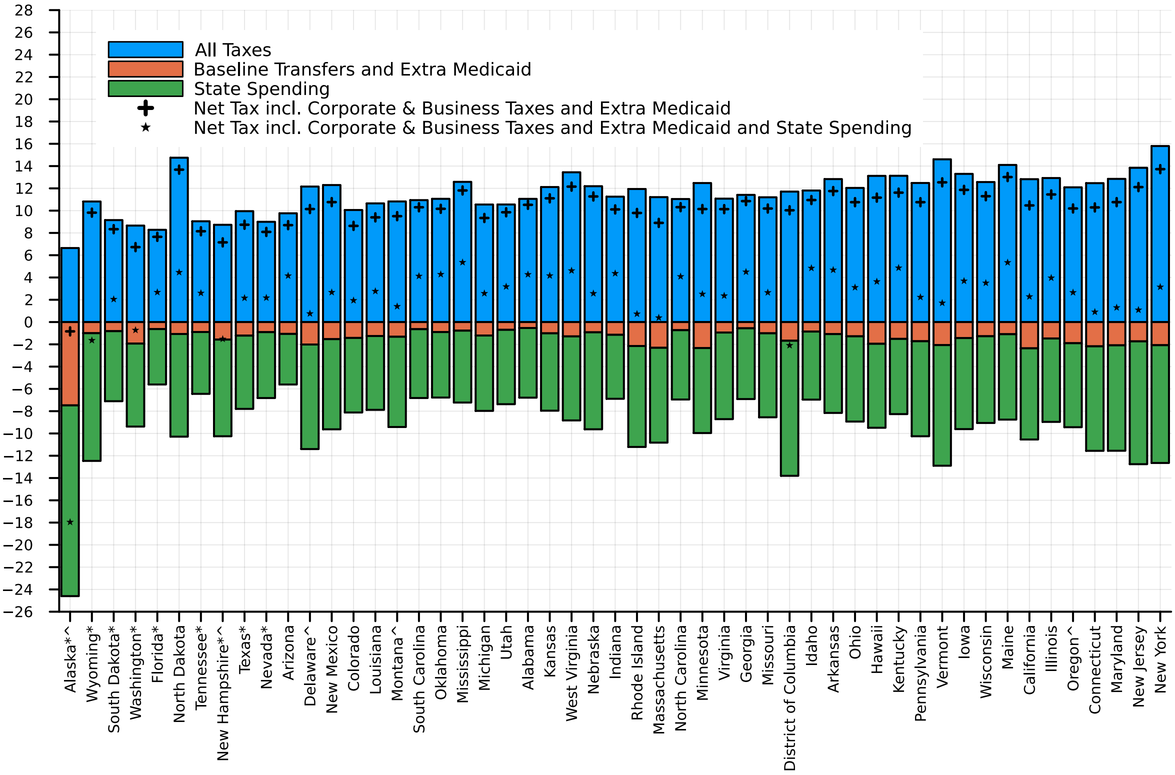

Figure N6: Average tax and transfer rates by state. Baseline sample, 2015/2016. See notes to Figure 14.

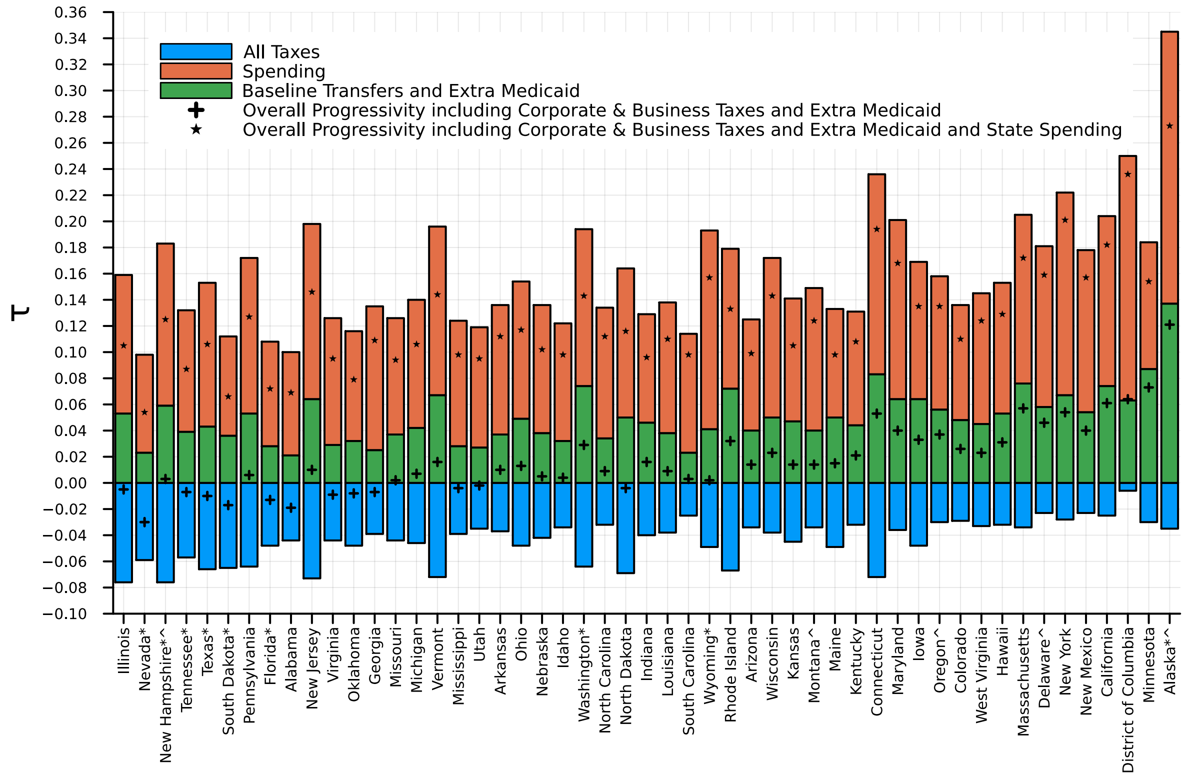

Figure N7: State progressivity decomposition. The plot shows estimates for progressivity induced by each of the state level taxes and transfers indicated in the legend, considering one at a time. Baseline transfers are as in Section 4.3. "All Taxes" is baseline taxes plus corporate income and business taxes. See notes to Figure 17.

such as marital status, the number of children in the household, disability and employment status, and so on. Because our simple tax and transfer function does not perfectly fit the data, estimates for the progressivity parameter τ will depend on how the estimation procedure trades off misses between predicted and actual net taxes paid at different income levels.

O.1 PPML Estimates

König (2023) argues that when our net tax function is specified in a stochastic form with an idiosyncratic error, estimation via log least squares will deliver consistent estimates of the progressivity parameter τ only when the variance of this error varies in a particular way with the level of pre-government income (see also Silva and Tenreyro 2006). He therefore proposes an alternative approach to estimation in levels, which chooses λ and τ to solve

$$\sum_{j=1}^{J}(\tilde{y}_j - \lambda y_j^{1-\tau})y_j = 0,$$

where y_j and $\tilde{y}_j$ denote pre-government income and disposable income for household j. This is known as Poisson pseudo-maximum likelihood (PPML). Relative to our log least squares approach, the PPML approach effectively penalizes more (less) heavily a poor fit at relatively high (low) values for pre-government income. The reason is that log OLS minimizes *percentage* differences between predicted and actual net taxes paid, while PPML minimizes *dollar* differences between the two. Recall that given our baseline OLS estimates, the fitted HSV tax and transfer function implies net taxes that are too high at high income levels (see Figure 10). The PPML approach delivers generally lower τ estimates, which translates to lower net taxes and a better fit at higher income levels (at the expense of a worse fit at the bottom).

Figure O1 compares PPML estimates for state and local taxes and transfers to the log OLS estimates reported in the paper. The PPML estimates are closer to zero than the log OLS estimates, as expected, but the rank correlation between the two is high (0.82).

O.2 A More Flexible Functional Form for Net Taxes

Note, however, that the fact that actual log income after taxes and transfers is not quite a linear function of log pre-government income poses a more fundamental challenge to the simple HSV tax function. The only way to address this evidence of mis-specification is to estimate a more flexible function. Boar and Midrigan (2022) and Ferriere, Grübener, Navarro, and Vardishvili (2023) show that the fit to actual net taxes paid can be significantly improved by 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

$$y - T(y) = \lambda(y)^{1-\tau} + Tr, \qquad \text{(O1)}$$

where redistribution now depends on both the progressivity coefficient τ and the lump-sum transfer Tr. We label this specification HSV-T. The HSV-T specification directly addresses a mechanical limitation of the simpler HSV function,

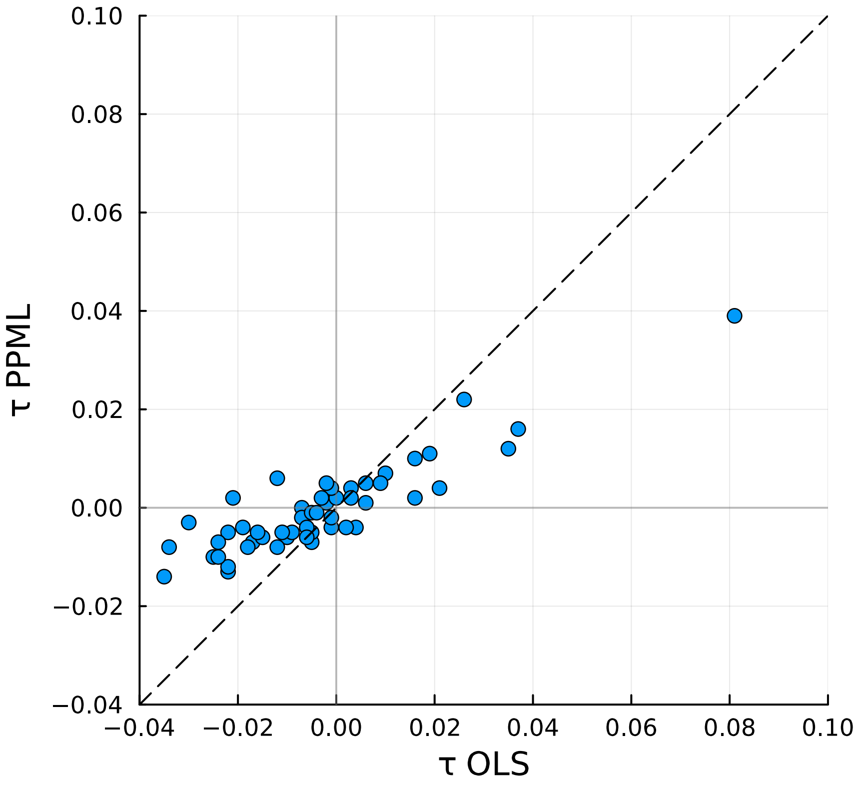

Figure O1: State progressivity estimates for 2015/2016. For each state, the x axis value reports τ_s estimated by log OLS, while the y axis values reports τ_s estimated by PPML.

which is that under HSV-T, $T(0) = -Tr$, while under HSV, $T(0) = 0$.

Using non-linear least squares, we have estimated state-specific values for the three parameters of the HSV-T specification, $\{\lambda_s,\tau_s,Tr_s\}$. We find generally positive values for Tr_s — which allow the model to better match low net taxes paid at low income levels — and lower values for τ_s — which allow for a better match to net taxes paid at high income levels.

O.3 Guide to Using Our Estimates

For each of our sample year pairs (2005/06, 2010/11 and 2015/16), the spreadsheets on our webpage contain five sets of progressivity estimates for our baseline tax and transfer specification (see Sections 3 and 4).[113] The estimates differ regarding the sorts of taxes and transfers included in household disposable income:

1. **agg_state**: includes state and local taxes and transfers.
2. **federal**: includes federal taxes and transfers.
3. **federal_agg_state**: includes federal, state and local taxes and transfers.
4. **state**: includes state and local taxes and transfers.
5. **state_federal**: includes federal, state and local taxes and transfers.

Estimates 1, 2, and 3 provide aggregate U.S. progressivity estimates and are constructed using the original ASEC

[113] https://github.com/jo-fleck/federal_state_progressivity

household weights. Estimates 4 and 5 provide state-level progressivity estimates for each U.S. state and the District of Columbia, and are based on adjusted ASEC household weights (see Appendix I).

The files in turn contain three sets of parameter estimates, corresponding to the following three models:

- HSV estimated by OLS
- HSV estimated by PPML
- HSV-T estimated by non-linear least squares

Note that the parameter τ is independent of the scale of the economy. In contrast, the parameter λ and the parameter Tr in the HSV-T specification do depend on the scale. We therefore report two values for λ. One is the λ estimated using nominal current dollar values for pre- and post-government income. The second λ value reported for each state s is $\hat{\lambda}_s = \lambda_s \times Y_s^{-\tau_s}$, where Y_s is average state household pre-government income. This $\hat{\lambda}_s$ is interpretable as the λ_s value that one would estimate if both pre- and post-government income are expressed relative to average state pre-government income. In particular,

$$\begin{aligned}\frac{\tilde{y}}{Y_s} &= \lambda_s Y_s^{-\tau_s} \left(\frac{y}{Y_s}\right)^{1-\tau_s} \\ &= \hat{\lambda}_s \left(\frac{y}{Y_s}\right)^{1-\tau_s}.\end{aligned}$$

Users of our estimates should either (i) scale model variables so that mean pre-government income is equal to one and set $\lambda_s = \hat{\lambda}_s$, or (ii) compute mean pre-government income $\bar{Y}_s$ in their data and set $\lambda_s = \hat{\lambda}_s \times \bar{Y}_s^{\tau_s}$.

We also report two Tr values: Tr_s, which corresponds to an estimate of nominal current dollar lump-sum transfers in state s, and $\widehat{Tr}_s = Tr_s/Y_s$, which corresponds to lump-sum transfers as a share of mean state household pre-government income.

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