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

Johannes Fleck† Jonathan Heathcote‡ Kjetil Storesletten§ Giovanni L. Violante¶

October 1, 2025

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, property and business taxes tend to have regressive tax systems and low average tax rates. States that are funded mostly by personal income and corporate income taxes tend to have progressive tax systems and high average tax rates. (v) Regressive states are concentrated in the South. (vi) State progressivity has remained broadly stable between 2005 and 2016. (vii) Including spending on public goods and services as a transfer has a large positive impact on measured federal and state progressivity. State spending on public education is associated with the largest increases in estimated progressivity.

Keywords: Economic Geography, Fiscal Policy, Public Redistribution, State and Local Taxes, Tax and Transfer Progressivity.

JEL Classification: E6, H2, H7, I3, R5

*An earlier version of this paper was titled "Tax and Transfer Progressivity at the U.S. State Level." We thank Bruce Webster, Daniel Lin and Katie Shantz for exhaustively answering questions on the Census Bureau Tax Model, the IPUMS team and Sarah Davis for answering questions on the ASEC, ACS and AHS datasets, Bilal Habib for helpful conversations on the CBO's Medicaid and Medicare imputation algorithms, and David Splinter for sharing their data and offering comments. We also benefited from conversations with and comments from Antonio Coran, Sebastian Dyrda, Amy Finkelstein, Giuseppe Fiori, Luciano Greco, Charles Hokayem, Jeff Larrimore, Gina Li, Byron Lutz, Karel Mertens, Amanda Michaud, Gaston Navarro, Valerie Ramey, Kim Rueben, Jon Steinsson, Arndt Weinrich, Matthias Wrede, Rui Yu, Fang Yang, and Owen Zidar. Participants at numerous seminars, conferences and workshops as well as four anonymous referees provided helpful suggestions. Knut Heimdal , Jiaxi Tan, Sarolta Vida, Hans Christian Wika, Yinjie Yu and Melanie Qing provided excellent research assistance. Fleck and Storesletten gratefully acknowledge financial support from the Research Council of Norway grant 316301. Fleck worked on this project while he was visiting the Economics Department at the University of Oslo and the Opportunity & Inclusive Growth Institute at the Federal Reserve Bank of Minneapolis. He is grateful for their hospitality. The views expressed herein are those of the authors and not necessarily those of the Board of Governors of the Federal Reserve System or the Federal Reserve Bank of Minneapolis.

†Corresponding Author; Board of Governors of the Federal Reserve System; johannes.fleck@frb.gov

‡Federal Reserve Bank of Minneapolis and CEPR; heathcote@minneapolisfed.org

§University of Minnesota and CEPR; kstoresl@umn.edu

¶Princeton University, CEBI, CEPR, IFS, IZA, and NBER; violante@princeton.edu

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 geographies in how much redistribution the combined federal and state tax and transfer system delivers.

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, as well as corporate income and business taxes. On the transfer side, we include a comprehensive set of programs, featuring both welfare (means-tested) and entitlement programs.[2] In an extension, we also consider spending on public goods

[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,

and services as transfers.

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, federal and state income taxes for each household are imputed by the Census Bureau tax model. We impute sales and excise taxes using federal and state-level data on sales tax rates and revenue from excise taxes, 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.

The U.S. social safety net is geographically fragmented as states and local governments set parameters determining the accessibility and generosity of many transfer programs. Our analysis carefully accounts for the resulting geographic heterogeneity in tax rates at the lower end of the income distribution. For instance, 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 under-reported 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

Social Security entitlement benefits, such as Medicare, are linked to *lifetime* income.

of the years we study. We therefore use SOI state-level data to impute incomes and taxes to households above a high income threshold.

In an extension, we broaden our transfer measure by including estimates of the transfer value of government spending on public goods and services. Thus, we can provide estimates of federal and state progressivity that reflect the totality of national and 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, on average, state and local tax and transfer systems are close to proportional. 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, property and business 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.

Our paper is related to several strands of literature in public economics. First, while there is a large set of papers aiming to measure redistribution through the overall tax and transfer system, there are fewer results on state heterogeneity. 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. Measuring redistribution based on Lorenz curves, he found 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. Yet, his analysis stepped short of providing summary measures at the level of specific states.

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). Our results go beyond those of these earlier studies in that we separately characterize federal and state-level progressivity. Thus, our estimates are of particular interest to a large and growing body of research which exploits geographic variation in exposure to federal fiscal policies.[3] While this research typically abstracts from policy differences at the sub-federal level, we characterize them in set of succinct estimates.

Our work is also related to papers studying the evolution of U.S. tax and transfer progressivity over time. For example, 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.

Relative to these studies, 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 some 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”. However, this index loads heavily on the top marginal rate of state income taxes, its construction excludes all transfers, and ITEP's methodology is proprietary.

Similar to ITEP, earlier papers aiming to measure state-level redistribution studied a narrow subset of state taxes and omitted 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) document 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

[3] See Chodorow-Reich (2019) for an overview.

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. Moreover, we include a large set of cash and in-kind transfer programs, most notably Medicare and Medicaid, and carefully model geographic benefit heterogeneity. In an extension, we broaden the notion of transfers to also account for public spending. 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.

Finally, our work is related to two influential papers, Piketty, Saez, and Zucman (2018) and Auten and Splinter (2024). These papers combine confidential administrative data from tax records with data from the national accounts to construct detailed estimates for the distribution of income, taxes, and transfers. Notably, this approach allows them to account for income components which are known to be either missing or under-reported in surveys and tax returns. In constructing our dataset, we pursue a similar strategy, and we inflate various components of income to replicate their aggregate counterparts in national income. We compare the distribution of tax rates and transfers across the income distribution that we estimate to the ones from those papers. We find net tax rates at the top of the income distribution that are slightly higher than those reported by Piketty, Saez, and Zucman (2018) and slightly lower than those in Auten and Splinter (2024). In contrast to these two studies, the distribution of income, taxes, and transfers in our analysis is constructed entirely from publicly available data. Two other distinguishing features of our analysis relative to those papers are our emphasize on cross-state heterogeneity in taxes and transfers, and our more detailed analysis of the extent of redistribution embedded in transfer programs and government spending, as discrepancies between states are especially large there.

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 illustrates the variation in tax levels and tax progressivity across U.S. states for the three different sample years we study and investigates correlates of the variation in progressivity. In Section 5, we present extended measures of progressivity that also include 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

2.1 Primary data sources

Our primary data source is the Annual Social and Economic Supplement (ASEC, ”March Supplement”) to the Current Population Survey (CPS). 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.[4]

One limitation of the ASEC survey for measuring income received and taxes paid is that income and tax variables are top-coded in the publicly-available version. In addition, as we describe further below, business and asset income are under-reported in the survey. These limitations are problematic 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 revenue.[5]

We therefore 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 (income before taxes and transfers) 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.[6] We label our household data set after this replacement exercise our ASEC+ sample.

One of the many differences between our measurement approach and those of Piketty, Saez,

[4] We pool observations over adjacent years to increase sample size. Figure D1 in Appendix D.1 shows that, for all of our sample years, we have no fewer than 500 households in each state in our sample.

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

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

and Zucman (2018) and Auten and Splinter (2024) is that we rely on the ASEC survey to measure income and taxes for most households, and use tax return data only to estimate incomes and taxes at the top. In contrast, those authors rely on tax returns across the entire distribution. There are pros and cons to both approaches. Some attractive features of the ASEC survey are as follows. First, it is designed to cover the entire U.S. population – not just households who file taxes. Second, it is based on the natural unit of households, rather than on tax filers. Third, ASEC asks about all income, including non-taxable income. Fourth, ASEC includes comprehensive measures of transfers, which will be an important component of our analysis of overall tax and transfer progressivity.[7]

2.2 Income Measurement

The income concept that we will adopt as our baseline is national income as measured in the National Income and Product Accounts (NIPA), which is also the starting point for the income measures used by Piketty, Saez, and Zucman (2018) and Auten and Splinter (2024). It is well known that aggregate income as reported in the ASEC survey and in the IRS-SOI data falls far short of aggregate NIPA national income. The main reason for this is that the national income concept is broader. First, NIPA national income includes taxes on production and imports – which includes all sales taxes, excise taxes, and property taxes.[8] Second, NIPA national income includes all corporate profits, while the ASEC survey and the IRS SOI data miss the portion of those profits that are retained by firms rather than distributed. Third, NIPA national income includes, as part of rental income, estimates of owner-occupied rent.[9] Yet another conceptual difference is that compensation of employees in the NIPA includes the value of employer contributions to pensions and health insurance plans, while ASEC survey respondents are simply asked to report how much they earned.

In addition to these conceptual differences, income in the ASEC and the SOI is typically under-reported, implying that measured income falls short of NIPA values even for income categories that are conceptually similar. These shortfalls are most pronounced for business income and asset income (see, for example, Rothbaum 2015, and Imboden, Voorheis, and Weber 2023).

[7] In appendix D.4 we provide a detailed comparison between the distribution of net tax rates in our sample and in that of Piketty, Saez, and Zucman (2018) and Auten and Splinter (2024), respectively.

[8] Consider a firm that collects $100 selling goods and uses the revenue to pay workers $95 and to pay the government $5 in sales tax. The contribution to national income of this firm is wage payments plus sales tax collected.

[9] The NIPA conceptualize an owner-occupier as effectively running a business in which they earn a rent from living in the home they own. The value of this rent after subtracting property taxes is included in NIPA rental income. Those property taxes are then added to national income as part of NIPA taxes on production, thereby ensuring that national income includes the full pre-tax value of imputed rent.

Under-reporting in the IRS SOI is especially acute for business income, as documented, for example by Gale, Joshi, Pulliam, and Sabelhaus (2022).[10]

We will measure effective tax rates as taxes paid relative to household income, and we will say that a given tax is progressive if the effective tax rate is increasing in income. As Piketty, Saez, and Zucman (2018) have forcefully argued, if reported income is below "true" income as measured in the National Accounts, and if that gap rises with income, then estimates of tax rates based on survey or IRS reported income will be too high, especially at high income levels, and such estimates will therefore exaggerate true tax progressivity.

To address these concerns, we proceed as follows. First, we partition national income into five components that we can map between the ASEC, the SOI, and the NIPA in a consistent way. We label these components wage income, proprietors' income, asset income, owner-occupied rents, and taxes on production. The definitions of these components are outlined in Table 1. For the first three of these components, we compute ratios of per capita income values in the NIPA relative to their counterparts in our ASEC+ sample, and rescale the ASEC+ income measures by those ratios so that, by construction, our rescaled ASEC+ household sample replicates the corresponding aggregate NIPA target. Our approach here is similar in spirit to the more sophisticated but more complicated approaches followed by Piketty, Saez, and Zucman (2018) and Auten and Splinter (2024). For the last two components of national income (owner-occupied rents and indirect taxes) we do not rescale our ASEC+ estimates.[11] Some of our tax and transfer imputations will be based on the sum of wage income, proprietors' income and asset income, as recorded directly in the ASEC and SOI data. We will refer to this narrower income measure as "WPA income".

Wage income and proprietors' income are straightforward to compare across data sources. 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 ASEC and SOI wage income measures.

Our asset income category is measured less symmetrically across data sets and is largely a residual category that includes all components of income besides wages, non-corporate business income, owner-occupied rents and indirect taxes. We have already noted that one important distinction between NIPA measurement and the other data sources is that NIPA asset

[10]The NIPA measure for proprietors' income starts from net profits for proprietors and partnerships as reported to the IRS, but the NIPA then adds an adjustment for misreporting on income tax returns based on IRS audit data. In 2017, IRS net profits were $825bn and the upward adjustment for misreporting was $605bn (see NIPA Table 7.14).

[11]We do not rescale our household-level estimates for sales and property taxes to replicate NIPA counterparts, and thus rescaling the contributions of those taxes to income would be inconsistent.

Income Component	**ASEC**	**SOI**	**NIPA National Income**
Wage Income	wage income + estimated employer FICA	salaries and wages + estimated employer FICA	compensation of employees
Proprietors' Inc.	business income + farm income	business / profession net income	proprietors income
Asset Income	interest income + retirement income + dividend income + rents and royalties + private transfers + estimated cap. gains	SOI total income + untaxed pensions + untaxed interest - social security - UI benefits - salaries and wages - business net income	corporate profits + net interest + bus. current transfers + surplus govt. enterprises + rental income excluding owner-occupied rents
Owner-occupied Rents	Estimated owner rent		Owner-occupied rents + owners property taxes
Taxes on Production	Estimated sales + excise + customs taxes + business taxes + renters property taxes		Taxes on prodn. & imports less subsidies - owners property taxes

Table 1: This table summarizes our income definitions in each data source. In each case, household income is the sum of all five sub-components: wage income, business income, asset income, owner-occupied rents, and taxes on production.

income includes all profits, including retained earnings, while ASEC and the SOI only capture distributions.[12] Our rescaling procedure implicitly assumes that claims to retained earnings are distributed in proportion to measured asset income in ASEC+.

Realized capital gains are included in measured income for SOI households, but capital gains are not part of NIPA national income. Still, capital gains are an important source of income for high income households, and gains are taxed and thus matter for the distribution of taxes. In addition, realized capital gains are likely a good proxy for claims to corporate profits and for NIPA asset income more broadly. We have therefore chosen to include estimates for capital gains in our ASEC+ income measure. We use the SOI tables to impute estimates for capital gains to ASEC households below the $200,000 threshold for SOI replacement of income and tax

[12]NIPA asset income and SOI asset income both include income from S corporations. It is not clear where this income is reported in the ASEC survey. We implicitly assume that this income is either included in or is proportional to our total ASEC asset income measure.

variables.[13]

The majority of NIPA rental income is rents from owner-occupied housing. We adopt the following procedure for imputing owner-occupied rents to our ASEC+ household income measure.[14] First, following the nearest-neighbor procedure described below for imputing property taxes, we use information from the American Community Survey (ACS) to estimate home values and mortgage payments for homeowners in the ASEC survey. Second, we translate these mortgage payment estimates into estimates for outstanding mortgage debt. Third, we define home equity as the difference between home value and mortgage debt. Finally, we estimate the income flow from home equity as household home equity times an estimate of a rental rate minus a depreciation rate. See Appendix C for more details.

For the "taxes on production" component of national income, we estimate these taxes at the household level using the approaches described in the following sections of the paper. For each household we add to household income the sum of all federal, state and local sales, excise, customs and property taxes paid, including the imputed portions of those taxes paid by businesses.

Income Measure	**ASEC**	**SOI**	**ASEC+**	**NIPA**	**ASEC+/ASEC**	**NIPA/ASEC+**
Total Income	-	-	40,275	48,954	-	-
Wage and Salary	25,720	25,923	25,192	30,407	0.979	1.207
Proprietors' Income	1,358	1,150	1,278	4,170	0.941	3.263
Asset Income	3,124	10,411	8,438	9,097	2.701	1.078
Owner-Occupied Rents	-	-	2,778	2,187	-	-
Taxes on Production	-	-	2,589	3,093	-	-

Table 2: This table reports average per capita income values for all U.S. households for 2015/2016 and ratios between different data sources See Table 1 for income definitions.

Table 2 reports per capita income values in each data set we use and, in the last column, the scaling factors we apply to our ASEC+ sample. Per capita wage income and proprietors income are quite similar in the ASEC and SOI. Per capita asset income is much higher in the SOI than in the ASEC survey, and asset income is heavily concentrated at the top of the income distribution. Thus, when we replace ASEC WPA income measures for high income households with their

[13]In particular, we multiply ASEC household dividend income by SOI-based capital gains to dividend income ratios, where those ratios are state, year, and income-group specific. The SOI tables indicate that 86 percent of total realized capital gains accrued to households with AGI above $200,000 in 2016. The IRS reports annual summary statistics for the 400 tax returns with the highest Adjusted Gross Income. Capital gains typically constitute between half and two thirds of total income for these households.

[14]The ASEC survey does include an imputed rent estimate but that estimate has two limitations for our purposes: (i) it is top-coded at a relatively low value ($17,405), and (ii) the presented estimate is net of property taxes, while we want an estimate of income before taxes.

SOI counterparts to create our ASEC+ sample, we get much higher values for per capita asset income. When we inflate ASEC+ WPA values to match their NIPA counterparts, we boost wage and salary income by 21 percent, and asset income by 8 percent. But the component that is inflated the most is proprietors' income, which is scaled up by a factor of 3.3.

To recap, our income measurement procedure addresses the concern that our underlying ASEC data under-estimates income inequality at the top – and therefore exaggerates tax progressivity – in two ways. First, by replacing WPA income values for high income households with synthetic values from the IRS-SOI data we address the problem that the ASEC survey does not do a good job capturing asset income at the top, because of top-coding and under-reporting. Second, our rescaling to NIPA procedure further amplifies our measure of income inequality, because the income category that is inflated the most – business income – is also important at the top of the distribution.

Figure 2 illustrates the impact of these adjustments across the income distribution. This plot focuses on a sample of households of working age, as described in Section 2.5. The bars in the left panel show income shares for each of the ten deciles of the household income distribution, and for the top 1 percent of that distribution. The right panel shows, for the same bins, three ratios: (1) the ratio of average ASEC+ WPA income to average ASEC WPA income, which captures the impact of our SOI income replacement at the top, and (2) the ratio of average NIPA total income to average ASEC+ WPA income, which captures the impact of applying our rescaling procedure. The plot illustrates two points. First, our SOI income replacement strategy only changes measured income at the top of the distribution, but the effect is dramatic, with average income for the top one percent increased by a factor of 2.7. Second, when we adjust our ASEC+ WPA income measure to a measure consistent with NIPA national income as defined in NIPA (which involves rescaling WPA income, and adding owner-occupied rent and taxes on production) we amplify measured income across the income distribution. The effect of this adjustment declines mildly with income, because taxes on production and owner-occupied rent are larger shares of income for poorer households.

2.3 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), federal customs and excise taxes, federal corporate income taxes, and the federal estate tax. State and local taxes

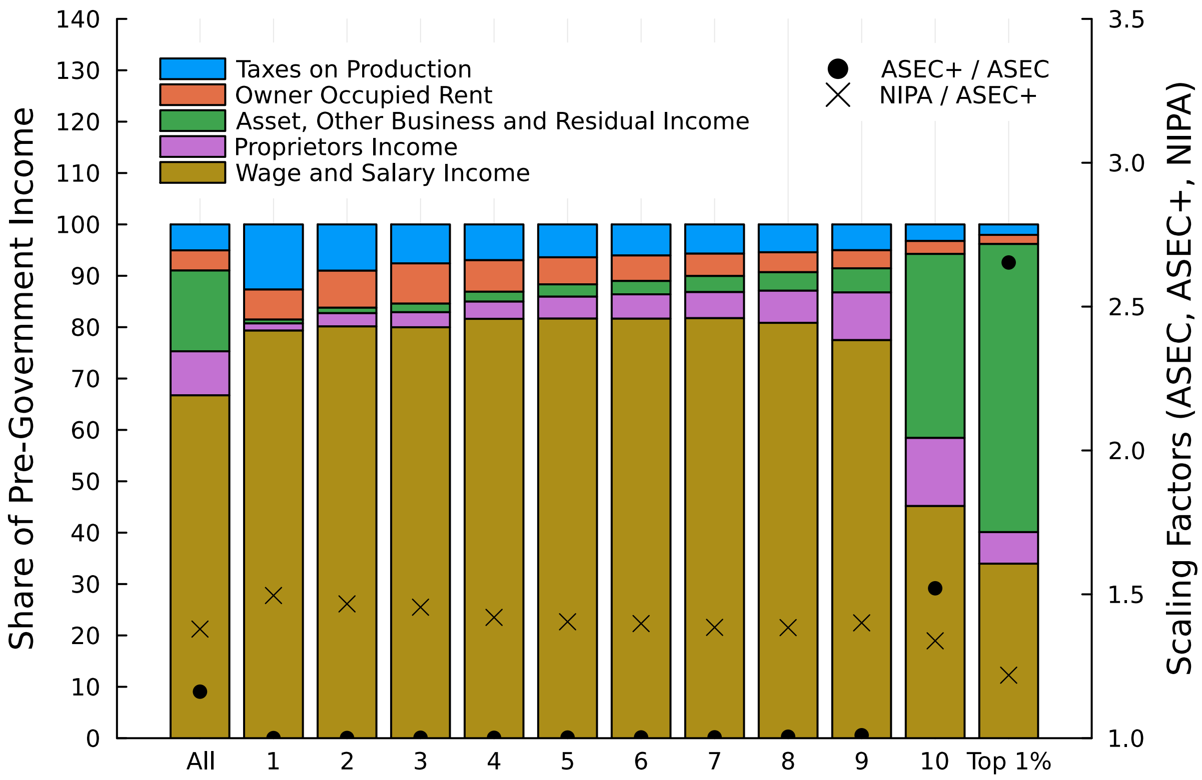

Figure 1: The bars in the figure shows the shares of our five components of household income for working-age U.S. households in 2015/2016. The first bar reports these shares for all working-age households, while the others report the shares for ten deciles of households ranked by income, and for the top 1 percent of that distribution. The dots and crosses show, for the same bins of households, the impact of replacing WPA income values for high income households with WPA values from the SOI (dots, right axis), and the impact of rescaling the WPA income components using the factors in the last column of Table 2 and adding the income components taxes on production and owner-occupied rents (crosses, right axis).

comprise personal and corporate income taxes, property taxes, sales taxes, excise taxes and user charges, state estate taxes, and business taxes (i.e., taxes collected from businesses, such as property as well as sales and excise taxes which apply to business purchases of goods and services).[15]

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.[16] 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

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

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

with AGI between $500,000 and $1m in 2016.

2.4 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).

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.

2.5 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 some labor force attachment. Specifically, we retain households where at least one spouse has at least an earned income equivalent to working full-year part-time (1,000 hours) at the federal minimum wage ($7.25 in 2016).[17]

Table 3 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.

	Federal Taxes and Transfers			**State & Local Taxes and Transfers**		
		Sample	All		Sample	All
Taxes	Income	10.72	10.33	Income	2.76	2.61
	FICA (employee+employer)	7.29	6.80	Business	2.61	2.53
	Corporate Income	1.99	2.05	Property	1.60	1.91
	Excise, Customs	0.44	0.50	Sales	1.08	1.19
	Estate	0.12	0.12	Excise	0.56	0.66
	ACA Shared Responsibility Payment	0.02	0.02	Corporate Income	0.35	0.36
	ACA Premium Tax Credit	-0.11	-0.13	Estate	0.03	0.03
Transfers	Medicaid* (cash value)	0.43	0.68	Medicaid* (cash value)	0.33	0.52
	Medicare (cash value)	0.39	3.13	Unemployment Benefits	0.11	0.12
	Social Security Disability and Survivors Benefits	0.28	0.62	Worker's Compensation Benefits	0.05	0.07
	Social Security Old Age Benefits	0.25	4.19	TANF*	0.01	0.02
	SNAP	0.23	0.43	Alaska Permanent Fund Dividend	0.01	0.01
	Veteran's Benefits	0.15	0.37			
	Disability Benefits	0.13	0.23			
	Pell Grant	0.13	0.16			
	SSI	0.12	0.35			
	Survivor's Benefits	0.11	0.32			
	School Lunch	0.08	0.08			
	Housing Assistance	0.06	0.24			
	ACA Cost Sharing Reductions	0.05	0.06			
	TANF*	0.01	0.02			
	Public Spending	6.53	7.44	Public Spending	9.45	9.81

Table 3: Federal, state and local taxes and transfers as shares of household income. 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. Average household income is $170,639 for households in our working-age sample and $124,271 for all households in the ASEC dataset. Transfers marked with an asterisk have both federal and state components.

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

2.6 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 ac-

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

curate measures of some income components (such as capital gains) as well as tax credits (such as the Earned Income Tax Credit (EITC) and Child Tax Credit), deductions, and exemptions.[18]

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.[19]

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 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 to our FICA tax measure. We also add this same amount to household wage income. 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 wage income.

Figure 2 plots income and payroll taxes paid as a share of household income, for different deciles of the household income distribution. In aggregate, income and payroll taxes collect around 21 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

[18] 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.

[19] 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 E for more details on local income taxes and our imputation procedure.

somewhat offset by the fact that FICA taxes are capped, and thus the effective FICA tax declines at the top of the income distribution.

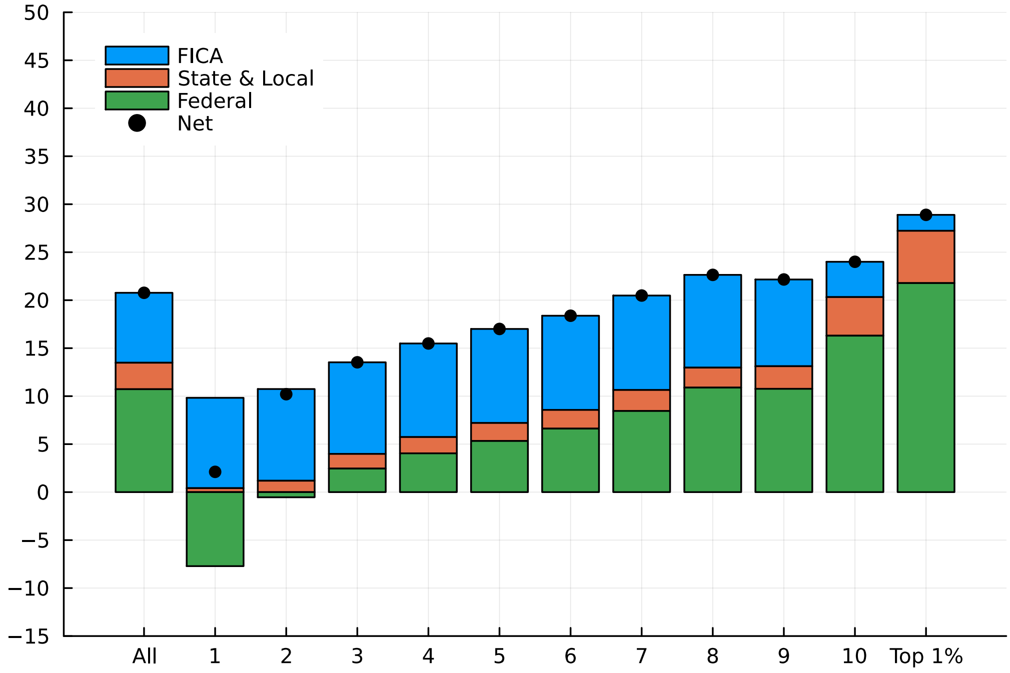

Figure 2: Average income tax rates (Federal, State & Local) and FICA tax rates for our ASEC+ working age sample, 2015/2016. Rates are plotted for all sample households, for 10 deciles of the household income distribution, and for the top 1 percent of households by income. For each bin, tax rates are computed as average taxes paid divided by average within-bin income. The tax and income values are reported in Table 5.

2.7 Sales and Excise Taxes

Households pay taxes on their consumption expenditures via sales and excise taxes. Most of this tax revenue accrues at the state and local level. The federal government levies excise taxes on a small set of goods, including gasoline, alcohol, and tobacco, plus customs on a broader range of goods. 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 – (i) imputed consumption spending, and (ii) 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 use these tables to impute consumption values for households in our ASEC+ sample. When doing so, we compare the sum of ASEC+ wage income, proprietors' income and asset income (WPA income) to CEX household income – these two income measures are conceptually similar. The CEX tables only report bin mean values for income and consumption. We use a piecewise linear interpolation scheme to infer a complete consumption schedule.[20]

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).[21]

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.[22] We apply these rates to most categories of goods, except for food consumed at home, drugs, and goods subject to excise taxes. Prescription and non-prescription drugs are almost universally tax-exempt, so we treat all healthcare spending as exempt from sales taxes. Food consumed at home is often untaxed or taxed at a reduced rate, and we use the food-at-home tax rates reported in the Book of States (BOS).[23] 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.[24] 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.

[20]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 mean income value for the lowest CEX income bin.

[21]Appendix F details the adjustment factors for each good and service.

[22]See, for example, Padgitt (2009).

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

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

We label these items as ”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 customs and 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.[25]. We assume the same split for taxes on public utilities.

Customs Duties We assume that 80% of federal customs duties are levied on consumption, corresponding to consumption's share of GDP. We assume that customs taxes apply proportionately to total household consumption expenditure. The customs tax rate is consumption's share of federal customs revenue divided by pre-tax consumer spending.

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 3 plots our estimates of sales and excise taxes paid for different deciles of the household 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 differ from the bundles consumed by richer households, and bundles that are more heavily taxed. Figure 4 illustrates both of these sources of regressivity. It

[25]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).

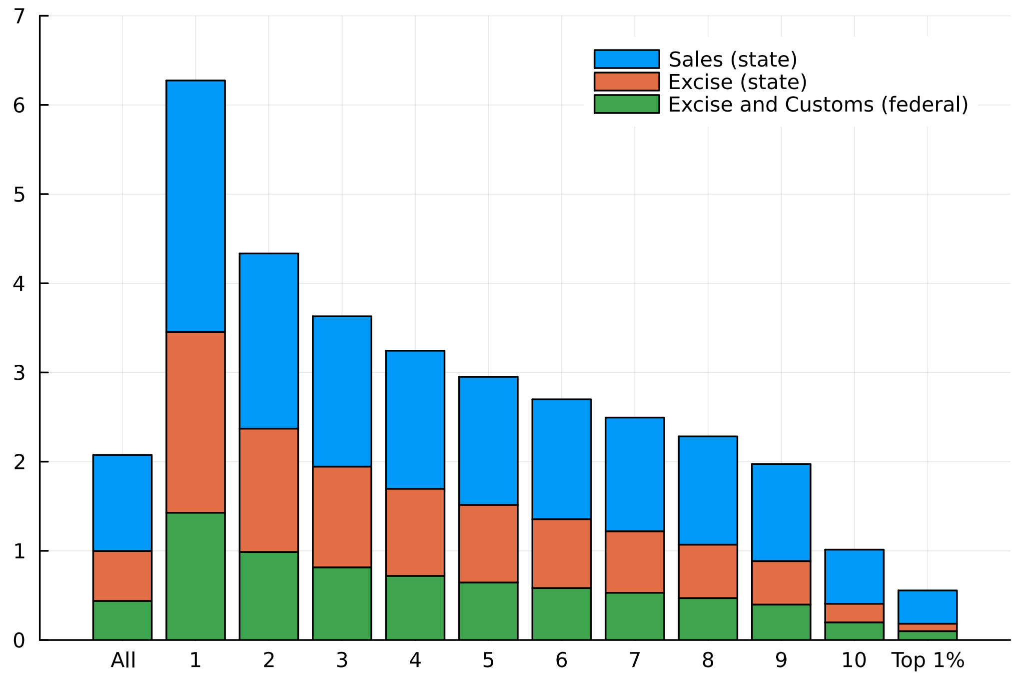

Figure 3: Average consumption taxes expressed as a share of household income for our working age sample in 2015/2016. See notes to Figure 2.

shows total household consumer spending as a share of household income and the effective consumption tax rate for different income deciles. The consumption tax rate plotted in this figure is computed as consumption taxes paid divided by pre-tax consumption expenditure.

Spending shares decline rapidly with 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, alcohol and tobacco are especially heavily taxed, and the shares of income devoted to these items decline very sharply with income.

Figure 4 shows that our measure of consumer spending exceeds income for low income households.[26] There are two reasons for this. First, households with low income have low savings rates, partly reflecting that the low-income state might be transitory. Second, the plot shows spending as a share of income before taxes and transfers. The lowest income deciles receive significant transfer income (see Section 2.12), which implies a lower consumption rate out of income inclusive of transfers and taxes.

[26]This is consistent with measurements in CEX. For example, households with an income before taxes between $5,000 and $10,000 had average annual expenditures of $21,014 in 2015-2016.

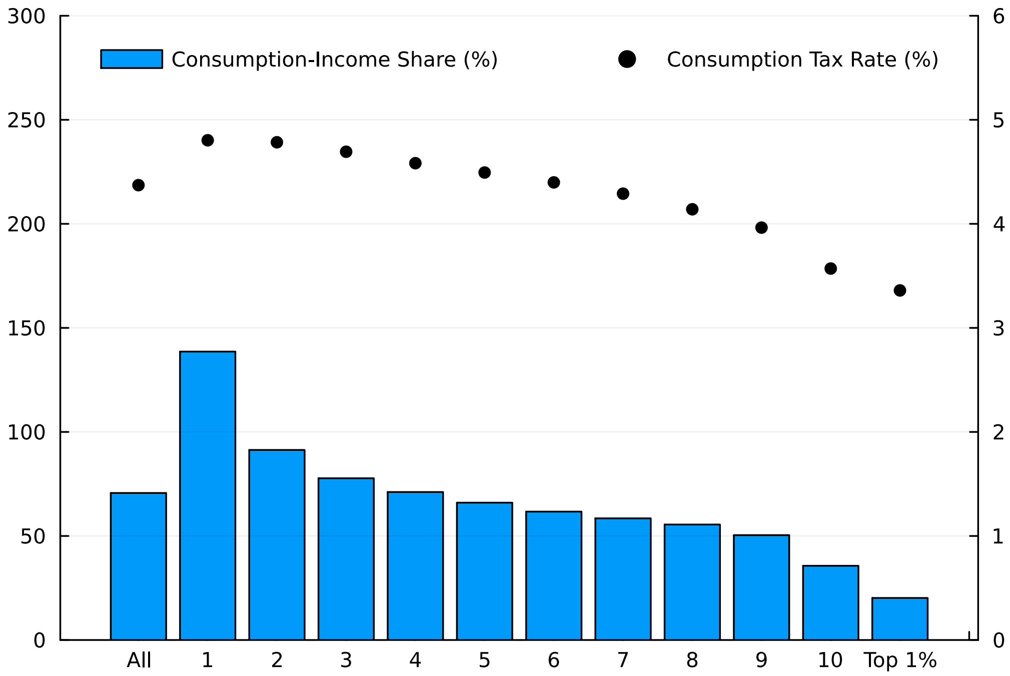

Figure 4: Average household consumption-income shares and consumption tax rates by income for our working-age sample in 2015/2016. Consumption-income shares (bars, left axis) are pre-tax consumer spending divided by household income. Consumption tax rates (dots, right axis) are consumption taxes paid divided by pre-tax spending. See notes to Figure 2.

2.8 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 the form of higher rents, a portion of the property taxes levied on rental property. Appendix G 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.[27] 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

[27]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.

(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, 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 G.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

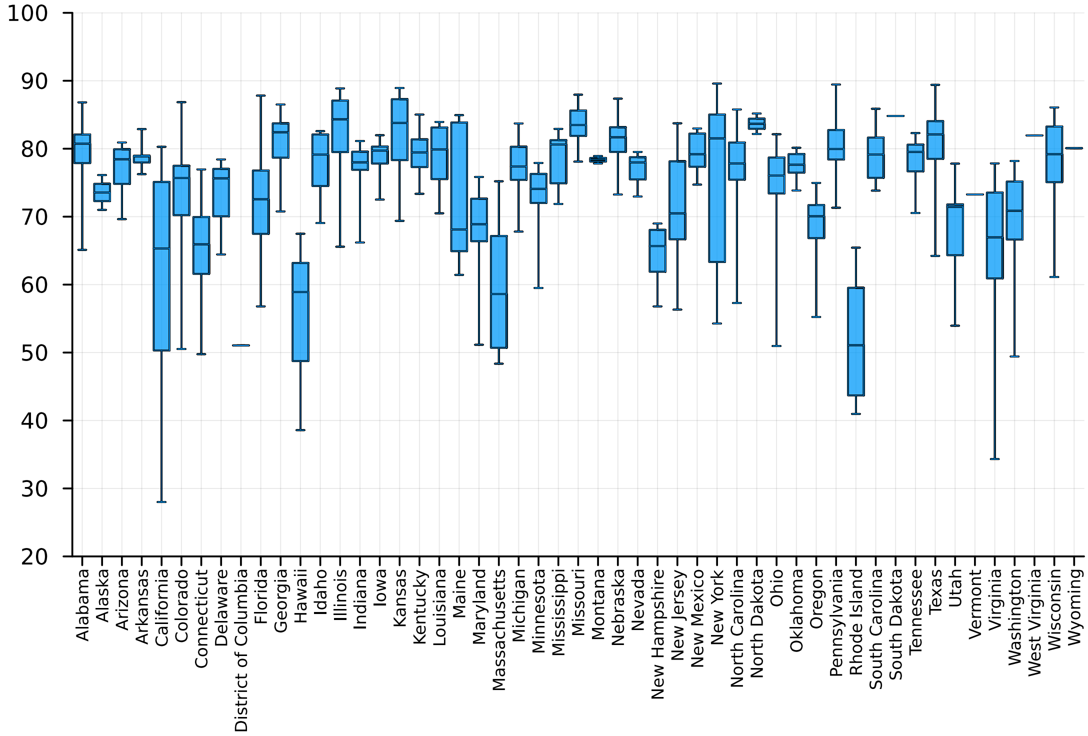

Figure 5: Property tax pass-through by county for 2015/2016, in percent. For each state, the outer ticks show the within-state range of estimated pass-through coefficients across counties. The shaded area plots the inter-quartile range across counties, while the line in the middle represents the median 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.

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 5 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 6 plots property taxes for owners and renters as a fraction of household income for different deciles of the household income distribution. It is clear that property taxes are regressive. Effective tax rates decline

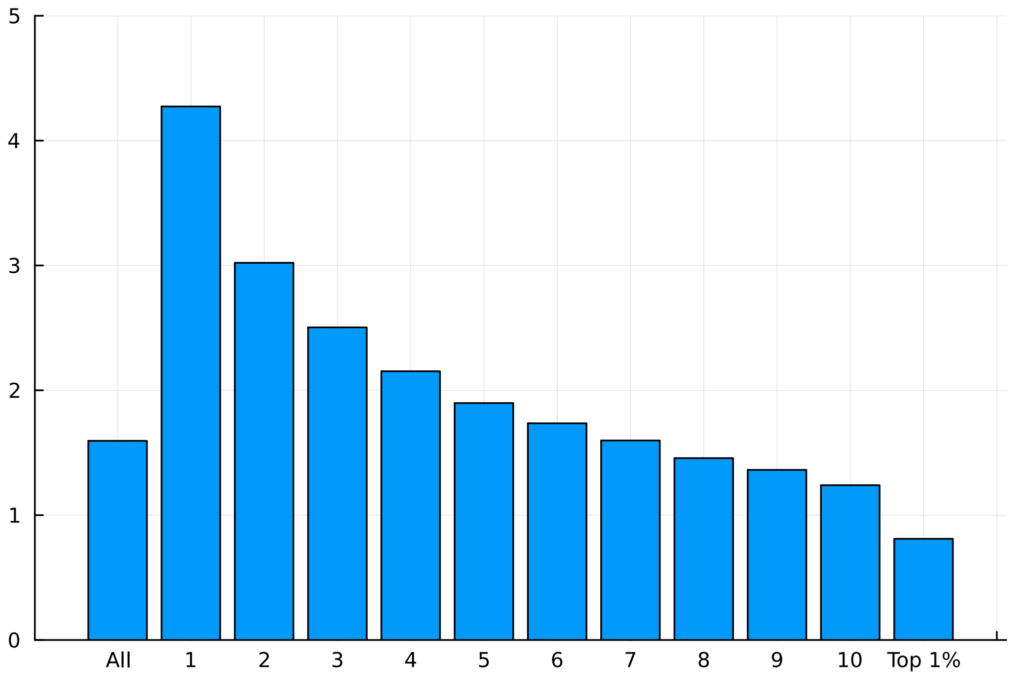

Figure 6: Average property tax rates for working-age households in 2015/2016. Includes homeowners and renters. See notes to Figure 2.

strongly with income; while property taxes claim at least two percent of income for the poorest 50 percent of households, they account for less than 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 property taxes than homeowners (as shown in Table 5).[28]

To understand the source of property tax regressivity, consider Figure 7. It plots the relationship between mean home values and rents for different household 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.

[28]Table D1 in the appendix reports the share of homeowners by income group.

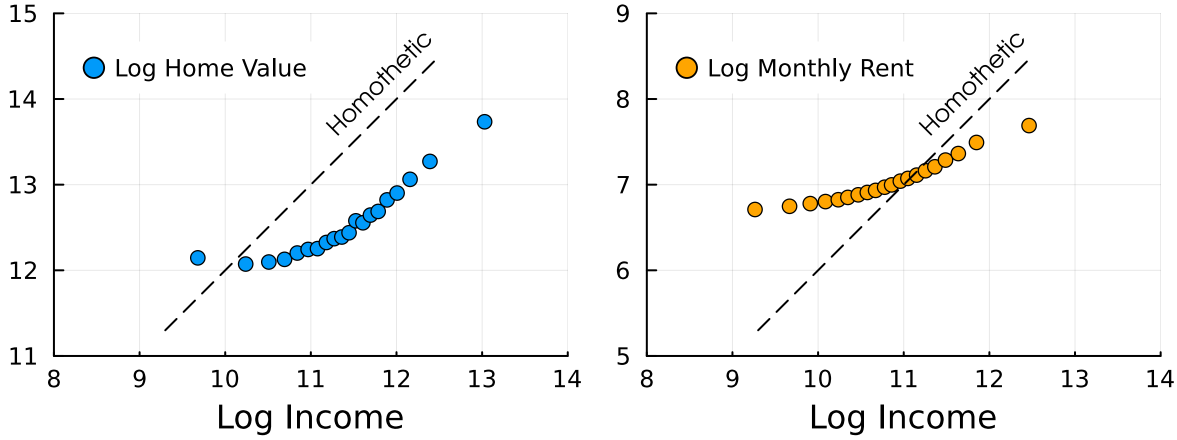

Figure 7: Home values (for owners) and rents (for renters) by self-reported WPA income (wage income plus proprietors income plus asset income). Each dot represents the average for a vingtile of households, where households are ranked by WPA income. Data source: ACS (2015/2016).

2.9 Comparing Imputed Taxes to External Estimates

A 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 H, we compare the total revenue we impute to each of these taxes to the revenue numbers reported there. 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 consumption tax revenue aligns well for most states, but tends to impute less tax revenue than the CSLG. [29]

2.10 Corporate Income and Business Taxes

The majority of corporate income tax revenue is collected by the federal government. Federal corporate income tax collections amounted to about 1.5 percent of U.S. GDP in 2016, while 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

[29]Note that we assume all spending in a given state is by state residents. Thus, we miss sales and excise taxes paid by non-residents (including tourists). Indeed, Hawaii and Nevada are two states for which our model underpredicts consumption taxes by large amounts.

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.

As these taxes are not paid directly by households, imputing them into our dataset requires making assumptions on how they are ultimately passed through from businesses 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 both in survey data and in tax returns, which are the source of the SOI state-tables we use to augment information on high-income ASEC households.

In what follows, we provide brief summaries on how we impute these taxes into our dataset, while Appendices I and J have more comprehensive descriptions.

Corporate Income Taxes Federal corporate income tax are mostly federal, even though 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.[30] 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 ge-

[30] 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).

ographically dispersed. However, we allocate the 40 percent of state corporate income taxes that falls on labor to households resident in the same state, in proportion to household labor earnings, as described above.

Figure 8 reports the resulting effective corporate income tax rates across the income distribution. Given our incidence assumptions, these are very progressive taxes.

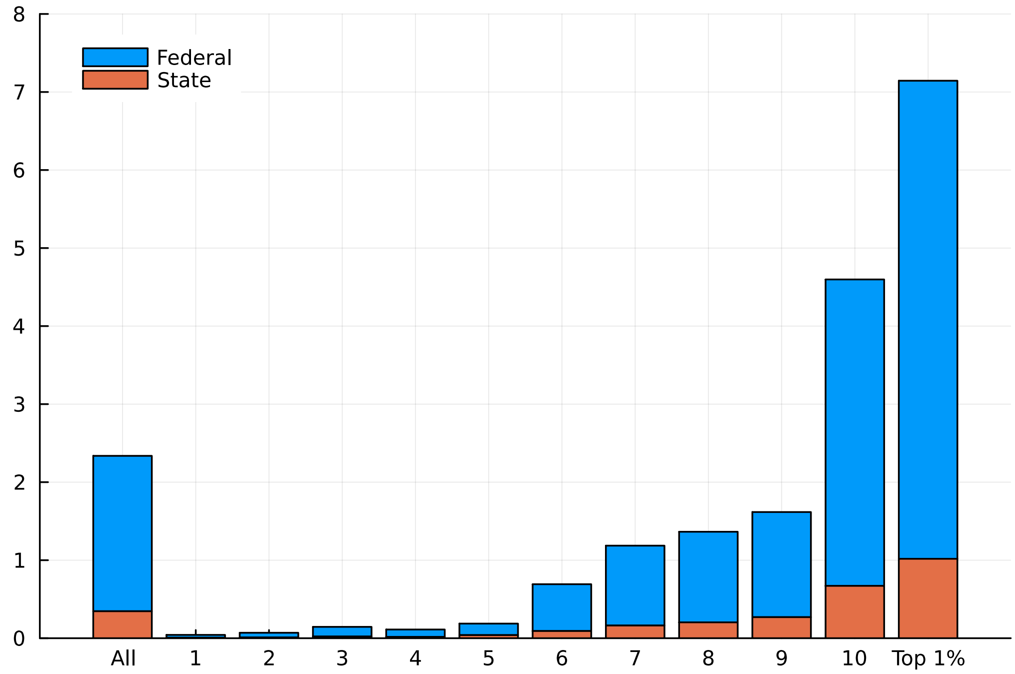

Figure 8: Average corporate income tax rates for working-age households in 2015/2016. See notes to Figure 2. The tax and income values are reported in Table D1 in Appendix D.2.

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 *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 2.8, 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. 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 J provides more details.

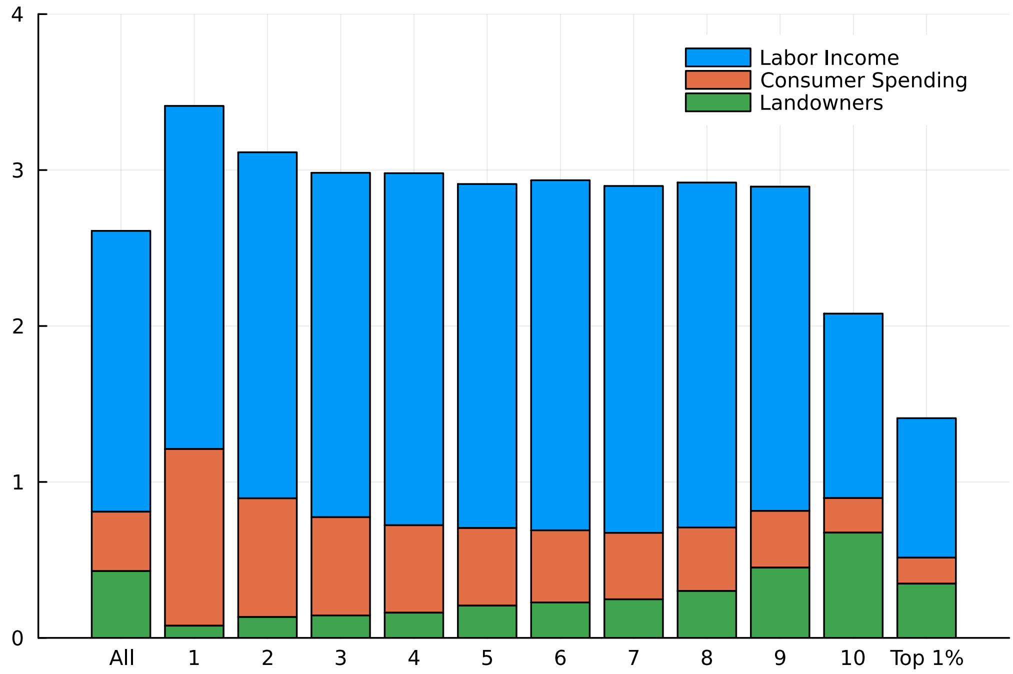

Figure 9: Average business tax rates for working-age households in 2015/2016. The plot decomposes taxes by their incidence on labor, consumer spending, and business income (a proxy for commercial property rental income). See notes to Figure 2.

Figure 9 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.

2.11 Estate Taxes

Estate taxes apply only to very large estates. For deaths that occurred in 2016, an estate was required to file a federal estate tax return if the gross value of the estate exceeded $5.45 million. Some states levy additional estate or inheritance taxes. In aggregate, the federal tax raises four times as much revenue as the state taxes. We conceptualize estate and inheritance taxes as being paid by the decedent. In contrast to taxes on production and imports, there is no direct income counterpart to estate taxes in the NIPA accounts.

Data on federal estate taxes paid is available from the IRS SOI Tax Stats web pages. We measure state estate tax collections using the Census Bureau State Government Tax Tables. We distribute estate taxes by income using the IRS Tax Stats Linked Estate Tax - Form 1040 Tables, which record 1040 Adjusted Gross Income for estate tax filers in the year before the filer died. These tables indicate that the federal estate tax is very progressive. In 2008, half of total federal estate taxes collected were paid by estates where the decedent reported AGI in excess of $500,000 in the prior year. However, since U.S. estate taxes are small in aggregate, including them only changes our progressivity measures by a very small amount. In particular, while we estimate that the top one percent of working age households paid $11,900 in estate taxes in 2015/16, on average, that is swamped by the $180,000 the same households paid in corporate income taxes (see Table 5). See Appendix K for more details regarding our estate tax imputations.

2.12 Transfers

Table 4 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.

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 a direct transfer. 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.[31] Social Security also has Survivors' Income

[31] 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.

Transfer Program	Federal	State	Source
Social Security Old-Age Benefits	x		ASEC, self-reported (INCSS, recipient age ≥ 62)
Social Security Survivor and Disability Benefits	x		ASEC, self-reported (INCSS, recipient age < 62)
Medicare	x		Imputed as described in Appendix M.7
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)
Pell Grants	x		ASEC, self-reported (INCEDUC/SRCEDUC); see Appendix M.4
Supplemental Nutrition Assistance Program	x		ASEC (CBO imputed); see Appendix M.1
Supplemental Security Income	x		ASEC (CBO imputed)
Housing Assistance	x		ASEC (CBO imputed); see Appendix M.3
ACA Cost Sharing Reductions	x		Imputed as described in Appendix L
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 M.5
Temporary Assistance for Needy Families	x	x	ASEC (INCWELFR); split as described in Appendix M.2
Medicaid	x	x	Imputed and split as described in Appendix M.6

Table 4: Assignment of each transfer program to federal and state budgets. For ASEC variables, the source column provides the IPUMS variable name.

and Disability Insurance components. These components are not reported separately in ASEC, which contains a single Social Security income variable. We therefore use age to split out the Old-Age component of Social Security. If a Social Security recipient is below age 62, we assume their eligibility is through 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 the Congressional Budget Office (Habib 2018) and impute benefit amounts using administrative data on Medicare-financed health expenditures per enrollee. To capture geographic benefit variation, we use state-level data on spending per enrollee, 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).

Other federal transfer programs we include are School Lunches, Veterans' Benefits, Survivors' Benefits, Disability Benefits, and Pell Grants. We take values for these transfers from the ASEC data (and adjust Pell Grants as described in Appendix M.4).

We use variables produced by the CBO imputation model for other federal transfers that are known to be under-reported in the ASEC survey.[32] These are the Supplemental Nutrition Assistance Program (SNAP), which provides food stamps, Supplemental Security Income (SSI), and federal housing assistance.[33] The CBO model also imputes Medicaid transfers, which we discuss below. In Section 2.13 we provide more details on the imputation of federal taxes and transfers related to the Affordable Care Act (ACA).

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).

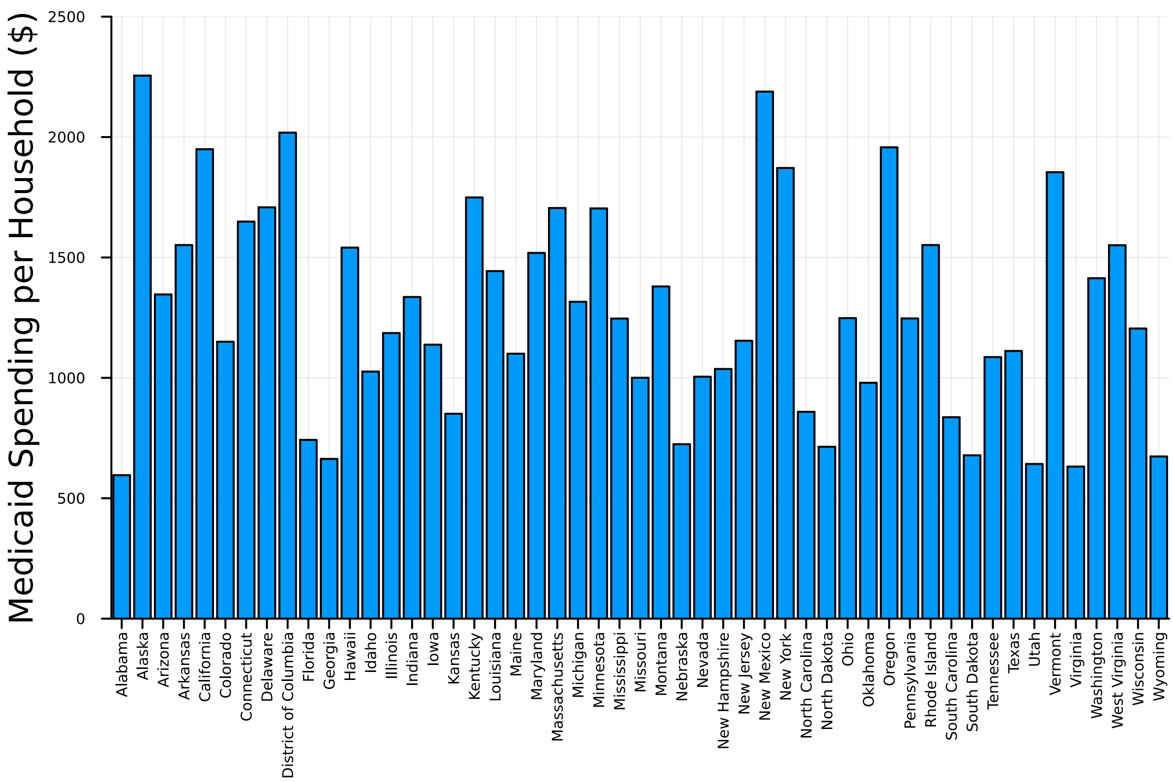

Figure 10: Cash values of state and federal average Medicaid spending per household in our baseline sample (2015/2016). Cross-state variation reflects a mix of variation in enrollment rates plus variation in spending per enrollee. See Appendix M.6 for details.

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

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

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 federal versus state spending shares. For TANF we rely on the self-reported value of transfers in ASEC.[34]

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.[35] Figure 10 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.[36]

Figure 11 plots transfer rates by income. Transfers are generally very progressive, as expected; total transfers exceed 30 percent of household income for households in the bottom income decile, while they are negligible for households at the top.

2.13 ACA-Related Taxes and Transfers

The Affordable Care Act (ACA) of 2010 introduced three new provisions that affect our estimates of federal taxes and transfers. All of them took effect in 2014, thus they only show up in calculations for years 2015/16.

[34] 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 M.2 for details.

[35] 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 uncompensated care costs.

[36] FMAP rates are based on state-level relative to national per capita income. See Appendix M.6 for more details.

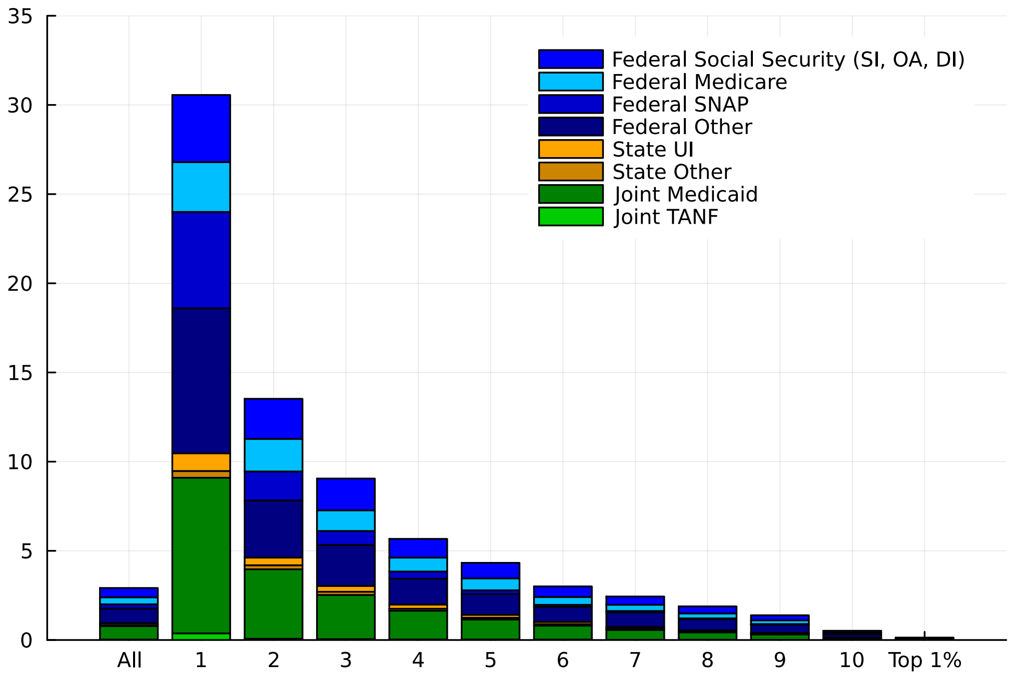

Figure 11: Average transfer rates for working-age households, 2015/2016. See notes to Figure 2.

The Premium Tax Credit (PTC) is a tax credit that eligible households receive when they purchase health insurance through the ACA marketplace. It has the goal of making individual health insurance affordable for middle- and lower-income households by subsidizing premia. Total spending on the PTC in 2015 was approximately $20bn. Individual Shared Responsibility Payments (SRP) are a federal tax penalty for not having minimum essential health insurance coverage or an exemption. This is a much smaller program than the PTC as total spending on the SRP in 2015 was only around $3bn. Finally, Cost Sharing Reductions (CSR) are federal subsidies that lower out-of-pocket health care costs such as deductibles, copays, coinsurance, etc. for low-income households. Aggregate spending on CSR in 2015 was around $9bn.

We treat PTC as tax credits and SRP as taxes, and we include them in our estimates of federal taxes. We treat Cost Sharing Reductions (CSR) as transfers and we include them in our estimates of federal transfers. Appendix L contains details on our calculations for these three ACA provisions.

2.14 All Taxes Net of Transfers

Figure 12 plots average net tax rates: the sum of all the taxes discussed above, minus the transfers plotted in Figure 11, divided by household income. For all working age households the average net tax rate is around 28 percent, but it varies dramatically by income. For households

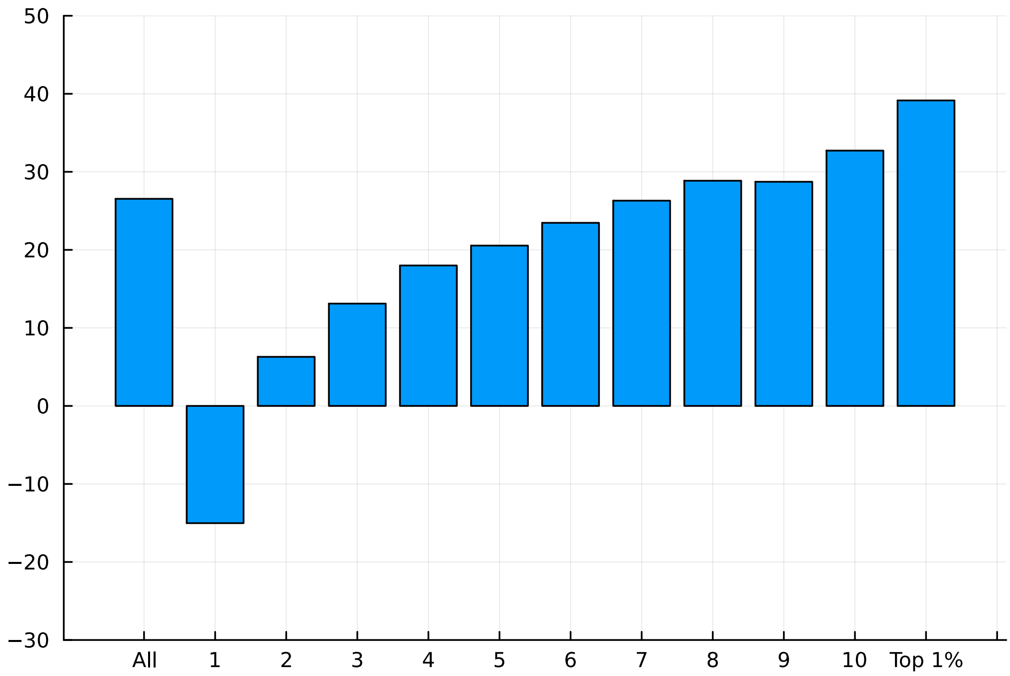

Figure 12: Average (federal and state) net tax rates for working-age households in 2015/2016. See notes to Figure 2.

with the lowest incomes, it is negative at about minus 15 percent, indicating that these households receive more in transfers than they pay in taxes. From the second income decile, the net tax rate is positive, monotonically increasing, and reaches a maximum of just below 40 percent for the households in the top 1 percent of the income distribution.

Table 5 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 D1 in Appendix D.2 is a more comprehensive version of this table. Table D2 in Appendix D.3 reports the corresponding statistics for the full dataset—that is, before dropping households that do not satisfy our age- and income-based sample selection criteria.

2.15 Comparing Our Distribution of Net Tax Rates to Literature Benchmarks

In this section we compare our estimated average tax rates net of transfers across the income distribution to Piketty, Saez, and Zucman (2018) and Auten and Splinter (2024). Additional details on these comparisons are contained in Section D.4.

Neither PSZ nor AS focus on the heterogeneity of state level tax and transfer policies, which is the main contribution of our paper. In addition, both of them utilize confidential administrative data, including individual tax returns, which are not accessible by the general public, while all

	All	1	2	3	4	5	6	7	8	9	10	Top 1%
Household Income	170,639	30,632	51,604	68,734	85,944	105,174	126,688	152,317	185,817	239,913	659,367	2,519,652
Wage and Salary Income	113,868	24,302	41,358	54,975	70,146	85,894	103,446	124,519	150,219	185,869	297,921	855,840
Business and Farm Income	14,622	428	1,334	2,012	2,888	4,492	6,004	7,734	11,625	22,289	87,404	154,786
Asset and Residual Income	26,840	229	548	1,152	1,651	2,520	3,292	4,776	6,693	11,257	236,141	1,412,917
Owner Occupied Rent	6,689	1,791	3,716	5,384	5,273	5,536	6,293	6,624	7,201	8,445	16,626	44,769
Taxes on Production and Imports	8,619	3,882	4,649	5,211	5,986	6,733	7,652	8,664	10,078	12,054	21,274	51,341
SOI Replaced (%)	8	0	0	0	0	0	0	0	0	0	84	100
Total Transfers	4,976	9,360	6,980	6,223	4,873	4,551	3,807	3,717	3,506	3,328	3,419	3,428
Federal Transfers	3,370	6,156	4,596	4,142	3,170	3,071	2,527	2,618	2,515	2,364	2,541	2,587
School Lunch	130	347	237	160	135	100	84	71	61	53	50	65
Veterans' Benefits	258	205	175	247	249	293	263	345	272	254	276	418
Survivors' Benefits	185	142	101	137	110	132	145	287	307	191	303	183
Disability Benefits	215	256	226	221	192	222	205	162	196	218	249	109
SS SI and DI Benefits	478	813	779	748	470	485	417	340	287	242	203	75
SS OA Benefits	422	342	385	481	435	435	344	372	460	446	516	699
SNAP	401	1,656	839	538	343	220	146	96	70	61	37	33
SSI	205	525	358	332	210	167	119	102	72	83	85	124
Housing Assistance	109	754	182	67	36	16	20	6	2	2	2	4
Medicare	666	855	941	797	673	703	551	538	513	509	585	666
ACA CSR	83	99	244	202	143	81	37	15	7	5	0	0
Pell Grants	218	162	129	211	174	219	197	284	270	299	235	211
State Transfers	281	420	337	350	294	275	268	247	204	231	188	101
Unemployment Insurance	187	304	222	223	198	169	161	157	141	161	135	73
Workers' Compensation	83	109	107	117	86	95	93	77	51	59	39	13
Alaska PFD	11	7	9	9	10	11	13	13	12	12	13	16
Joint Federal-State Transfers	1,325	2,784	2,046	1,732	1,409	1,205	1,013	852	787	733	690	739
TANF	31	113	35	30	20	23	22	17	23	12	13	28
Medicaid	1,294	2,672	2,011	1,701	1,389	1,182	991	835	764	722	677	711
Income Taxes	23,005	-2,237	335	2,738	4,933	7,580	10,852	16,212	24,106	31,472	134,013	686,094
Federal	18,299	-2,363	-278	1,687	3,474	5,606	8,386	12,877	20,242	25,822	107,496	548,817
State & Local	4,706	126	613	1,051	1,458	1,974	2,467	3,335	3,864	5,651	26,517	137,277
FICA	12,437	2,884	4,930	6,560	8,381	10,304	12,433	14,989	17,960	21,685	24,245	41,914
ACA PTC	-185	-241	-546	-492	-325	-145	-54	-24	-15	-8	0	0
ACA SRP	33	31	37	34	29	31	29	26	31	33	47	70
Estate Taxes	268	32	32	31	32	34	56	125	135	230	1,974	11,879
Federal	211	25	25	25	25	26	45	99	107	180	1,548	9,216
State	58	7	7	6	7	7	11	26	28	50	426	2,662
Consumption Taxes	3,542	1,922	2,236	2,495	2,787	3,104	3,420	3,799	4,242	4,735	6,681	14,001
Federal	746	437	509	559	617	677	737	806	872	951	1,297	2,487
State	2,796	1,485	1,727	1,936	2,170	2,427	2,683	2,993	3,370	3,784	5,384	11,514
Property Taxes	2,722	1,309	1,559	1,721	1,850	1,996	2,199	2,434	2,707	3,269	8,175	20,421
Owners	3,290	1,618	1,871	1,950	2,039	2,197	2,380	2,595	2,866	3,477	8,621	21,189
Renters	1,721	1,210	1,348	1,451	1,574	1,622	1,760	1,912	2,064	2,242	5,726	14,954
Corporate Income Taxes	3,988	14	36	100	95	197	878	1,807	2,536	3,879	30,316	180,016
Federal	3,398	11	31	85	81	155	760	1,559	2,157	3,232	25,891	154,373
State	590	2	5	15	15	42	117	248	378	647	4,425	25,643
State Business Taxes	4,454	1,044	1,607	2,049	2,560	3,061	3,718	4,413	5,427	6,943	13,712	35,499
Labor	3,073	674	1,145	1,518	1,940	2,320	2,844	3,388	4,110	4,989	7,801	22,523
Consumers	650	347	393	433	482	523	586	649	757	872	1,458	4,211
Property	731	24	69	99	139	218	288	377	559	1,082	4,453	8,765

Table 5: Incomes, 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 weights. "All" reports average values for the entire sample. "1" to "10" correspond to deciles of households ranked by household income. Each decile contains about the same (weighted) number of households. "Top 1%" refers to the one percent of households with the highest incomes. "SOI Replaced" refers to the share of households for whom income and tax variables are imputed using IRS SOI data.

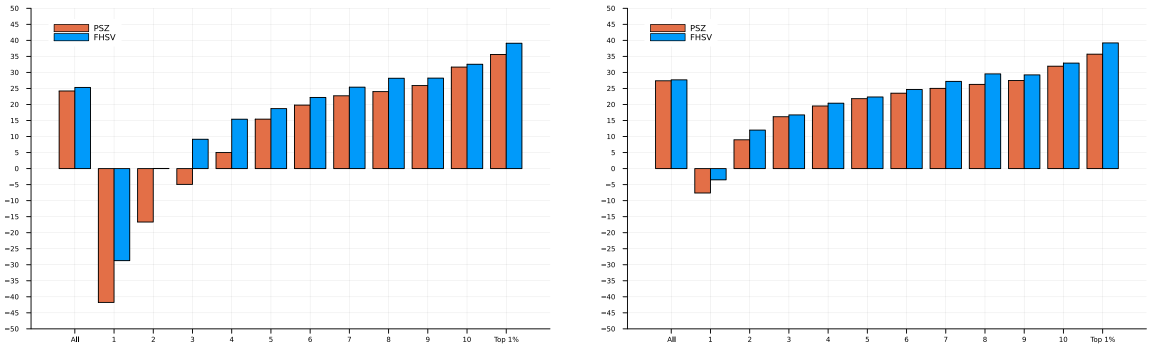

Figure 13: Comparison of our net tax rates (FHSV) to those of Piketty, Saez and Zucman (Piketty, Saez, and Zucman, 2018) for the years 2015/2016. Numbers for PSZ constructed from their micro data, available at `https://gabriel-zucman.eu/usdina/`. Left panel: Medicare and Medicaid valued at full cost in both samples. Right panel: Medicare and Medicaid excluded from both samples.

our calculations are based on publicly available data, and thus replicable from the bottom up, another methodological contribution.

Comparison to PSZ. In Figure 13, we compare the net tax rates of Piketty, Saez, and Zucman (2018), "PSZ" (red), and ours "FHSV" (blue) for income deciles one to ten and the top 1 percent of incomes. The left panel, where we include Medicaid (and Medicare) at full administrative cost, shows that average rates are remarkably similar and so are the net tax rates for incomes above decile five, with ours typically just a few percentage points higher. In deciles one to four, however, PSZ have notably lower (i.e. more negative) tax rates. This discrepancy is almost entirely caused by Medicaid transfers. When we exclude them in both samples (right panel), net tax rates line up much better below the median. There are several differences between our Medicaid imputation model and theirs both in terms of identifying eligible households and assigning transfer amounts.[37]

For the top one percent of households by income, we estimate higher tax rates than PSZ (39 versus 36 percent). This gap arises because we estimate higher federal income and corporate income tax rates at the top (+3 percentage points each), but lower consumption tax rates (-3 percentage points).

[37]PSZ impute Medicaid beneficiaries based on ASEC, and correct for under-reporting by blowing up multiplicatively the recorded number of beneficiaries across 40 bins of income deciles × marital status × above or below 65 years old to match the total number of beneficiaries from administrative records. Medicaid benefits are then imputed as a lump-sum amount per beneficiary. In contrast, as explained in detail in Section 2.12 and Appendix M.6, we do not just mechanically rescale the survey totals, but leverage a CBO algorithm especially designed to correct for the ASEC under-reporting in both the number of Medicaid recipients and the corresponding transfer amounts. In addition, we further refine the algorithm by modifying it to target state-level enrollment and state average spending, per enrollment group (Fleck, 2024).

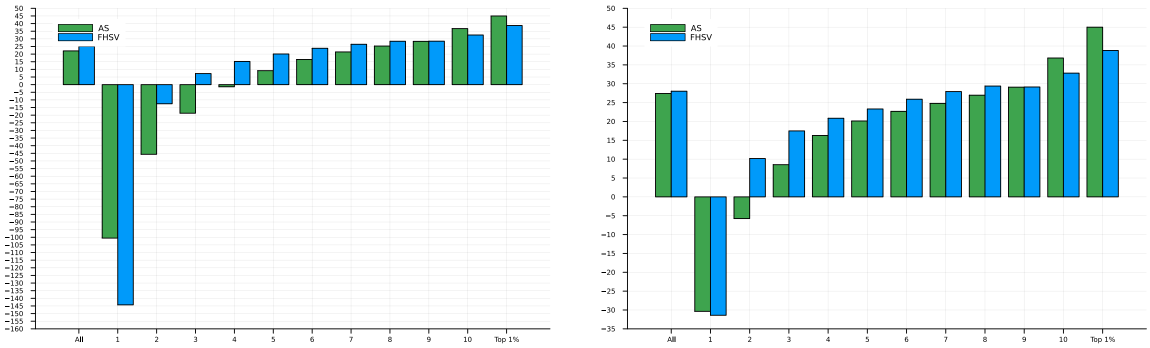

Figure 14: Comparison of our net tax rates (FHSV) to those of Auten and Splinter (2024) for the years 2015/2016. Numbers for AS refer to 25 to 60 years old individuals, provided by David Splinter. Left panel: Medicare transfers excluded. Right panel: Medicare and Medicaid transfers excluded from our sample, and non-cash transfers (which includes Medicaid) excluded from the AS data.

Comparison to AS. Figure 14 compares our calculations to those in Auten and Splinter (2024). Average net tax rates are very close in the two samples. The left panel, which includes Medicaid at full cost shows some notable discrepancies below the median, in line with our comparison with PSZ. Again, we believe our Medicaid imputation strategy is superior. Once we remove Medicaid transfers (right panel) differences become smaller. For the top one percent, our net tax rates are markedly below theirs (39 versus 45 percent).

Taking stock, because of the different data sources and different methodologies, a certain degree of misalignment between our measurement and these two papers should be expected. Yet, by comparing the total (i.e., federal and state) distribution of net tax rates in our sample to theirs, our results are broadly in line with theirs. For the top one percent of the national income distribution, which is the core of the AS and PSZ analyses, our estimates lie in between theirs. In contrast, our results point to somewhat higher net tax rates for the middle class than both of those papers.

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 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. In this specification, income after taxes and transfers, $y - T(y)$, is related to pre-government income y according to

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

where the coefficient $\tau \leq 1$ indexes progressivity.[38]

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.[39] 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.

Table 6 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 $\tau = 0.07$. Adding federal transfers raises τ to 0.135 and including federal excise taxes, corporate income taxes and ACA taxes gives an estimate of 0.149.

The next rows in the baseline panel isolate the progressivity embedded in state taxes and transfers. State income taxes, on average, are essentially proportional, while state transfers add a modest amount of progressivity. In contrast, property taxes, sales taxes, excise taxes and business taxes are all regressive. When all state and local taxes and transfers are incorporated in the measure of post-government income, the overall system appears proportional, with an estimated τ of 0.001.

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 0.161, which represents the overall progressivity provided by the entire U.S. tax and transfer system.[40]

---

[38] It is useful to note that $\tau = 0$ denotes a proportional system and $\tau > 0$ (< 0) 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.

[39] 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 working-age sample: we drop at most 0.07 percent of households.

[40] The baseline estimate in Heathcote, Storesletten, and Violante (2017) was slightly higher at $\tau = 0.181$. Their

Specification	Level	τ estimate	T_i measure
Baseline	Federal	0.070	Income Taxes
		0.135	- Transfers
		0.132	+ Excise & Custom Taxes
		0.132	+ Estate Taxes
		0.145	+ Corporate Income Taxes
		0.149	+ ACA PTC & SRP
	State	0.010	Income Taxes
		0.026	- Transfers
		0.016	+ Property Taxes
		0.009	+ Sales Taxes
		0.003	+ Excise Taxes
		0.003	+ Estate Taxes
		0.005	+ Corporate Income Taxes
		0.001	+ Business Taxes
	Federal & State	0.161	All Baseline Taxes and Transfers
Extension	Federal	0.166	- Extra Medicaid and Medicare
		0.174	- Education
		0.177	- Health
		0.178	- Veterans
		0.201	- Other
	State	0.019	- Extra Medicaid
		0.088	- Education
		0.096	- Health
		0.117	- Other
	Federal & State	0.283	Baseline - Extra Medicaid and Medicare - All Public Spending

Table 6: Estimates for aggregate progressivity from the pooled national working-age sample. See Table 4 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.” Extension includes spending on public goods and services. ”Other” denotes all spending not included in the listed categories. See Appendix P for details.

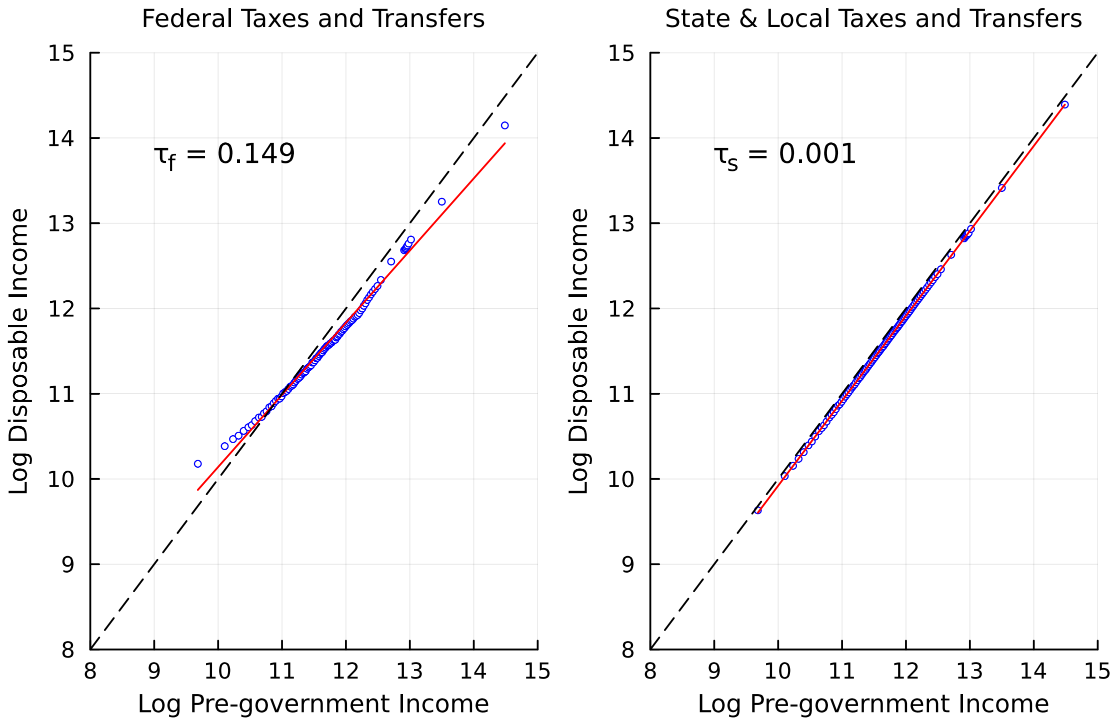

Figure 15: Fit of the HSV tax and transfer function. Left panel: T_i includes federal taxes and transfers. Right panel: T_i includes state and local taxes and transfers. Each dot corresponds to one percent of the 2015/2016 sample, ranked by pre-government income. Estimation uses ASEC household weights.

Figure 15 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 are too high at very low income levels (the bottom 5 percentiles) and and at very high income levels (the top 5 percentiles). 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 Q 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).

analysis included a smaller set of taxes and transfers. Their analysis was also based on reported ASEC WPA income, while in this paper we target a broader national income concept.

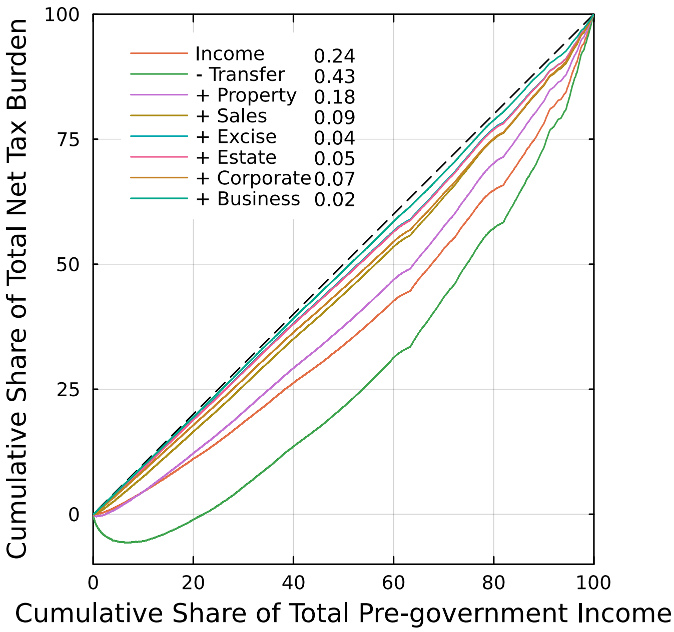

Figure 16: Lorenz Curves for the aggregate state taxes and transfers in Table 6. Suits (1977) index value shown next to each tax. Computed for our working-age sample in 2015/2016 using ASEC household weights.

For state taxes and transfers, we have also computed the Suits (1977) index, which is a non-parametric measure of progressivity. Figure 16 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 6. 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.[41] Adding property taxes moves the Lorenz curve up dramatically and reduces the Suits index value, confirming that these taxes reduce overall progressivity. Adding sales, excise, estate, corporate income and business taxes further reduces the index value, so that, on net, the sum of all state and local taxes and transfers

[41] 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.

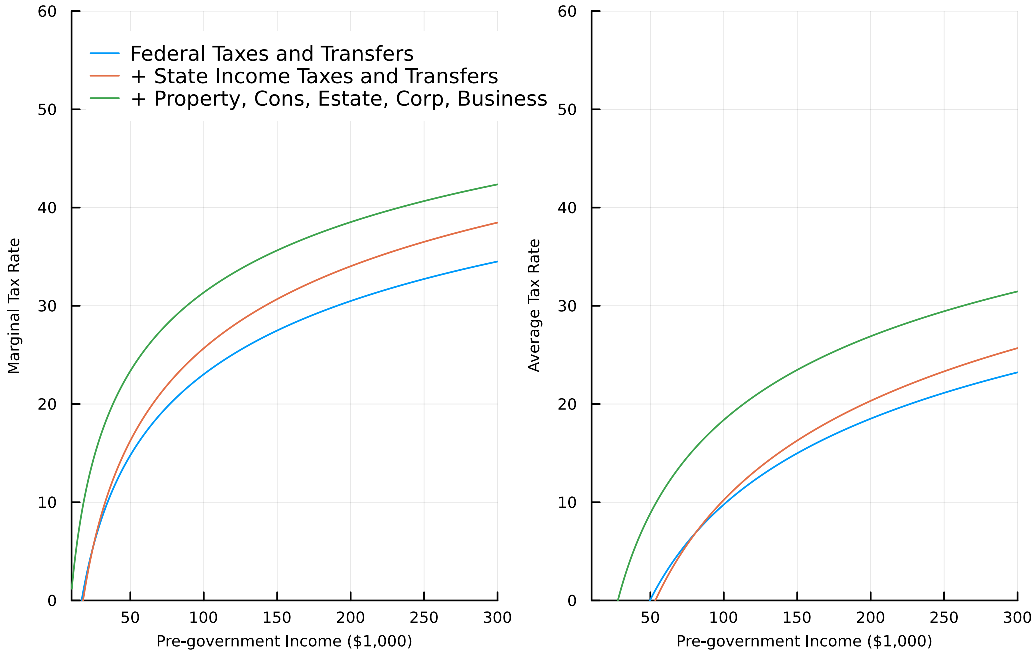

Figure 17: Average economy-wide marginal and average tax rate schedules for household incomes between \$10,000 and \$300,000, in percent, for different measures of taxes and transfers (see Table 6). Refers to 2015/2016.

amounts to a near proportional system.

Finally, to illustrate the implications of the τ estimates presented in Table 6 (and the corresponding λ estimates), Figure 17 translates them into profiles for marginal and average tax rate 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 regressive taxes in increase tax rates disproportionately at lower income levels.

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 household 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 15), 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 reweighted state income distribution for each state resembles the national distribution. In particular, we record household income values at each decile of the national household 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 N 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 18 plots state and local average rates for income taxes, sales and excise taxes, property taxes, and business and corporate income 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 19 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 income – is the sum of all these components. In both Figures 18 and 19 states are ordered left to right from the state with the lowest net tax rate (Alaska) to the one with the highest (New York).

The first clear message from these figures is that net tax rates vary substantially across states. Net taxes range from just above one percent of household income in Alaska to almost twelve 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.[42] None of the eight states

[42]State income tax revenue is not exactly zero in these states, because the IRS-SOI state-level tables indicate a small

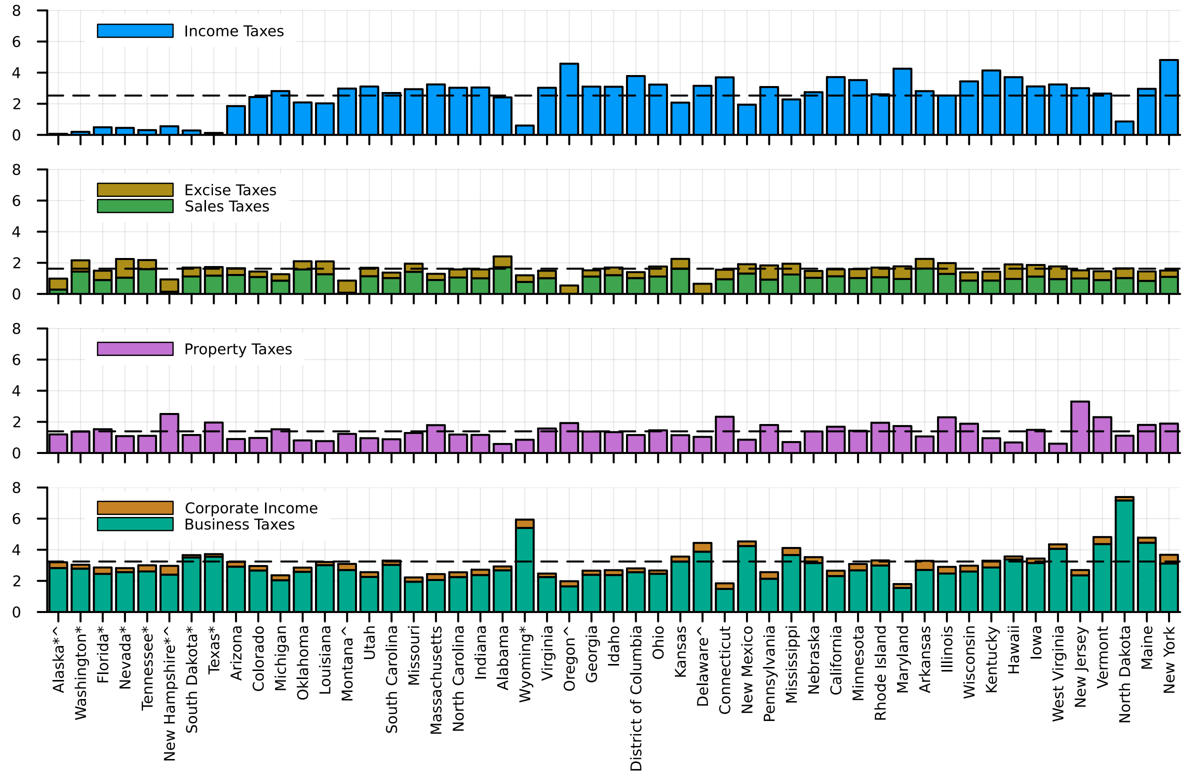

Figure 18: Average state and local tax rates by state in our working-age sample, 2015/2016. The horizontal dashed lines indicate national averages. A $*$ superscript denotes states that have no state income tax, and a $\wedge$ superscript denotes states that have no state sales tax. Computed after re-weighting households as described in Section 4.1. State estate taxes are small and not shown.

with the lowest overall net tax rates have a state income tax. Figure 18 illustrates that the states do not tax income do not appear to make up for lost income tax revenue via higher sales or property taxes. New Hampshire does have relatively high property taxes, but it also has no state sales tax.

Third, states that have sales taxes all collect quite similar shares of income via consumption taxes. The outliers are the "NOMAD" 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, Vermont, Illinois and Connecticut also raise substantial revenue from taxing property.

Fifth, taxes on business are an important source of revenue for most states, and especially for

but positive amount of state income taxes paid by high-income residents of these states. That is because 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.

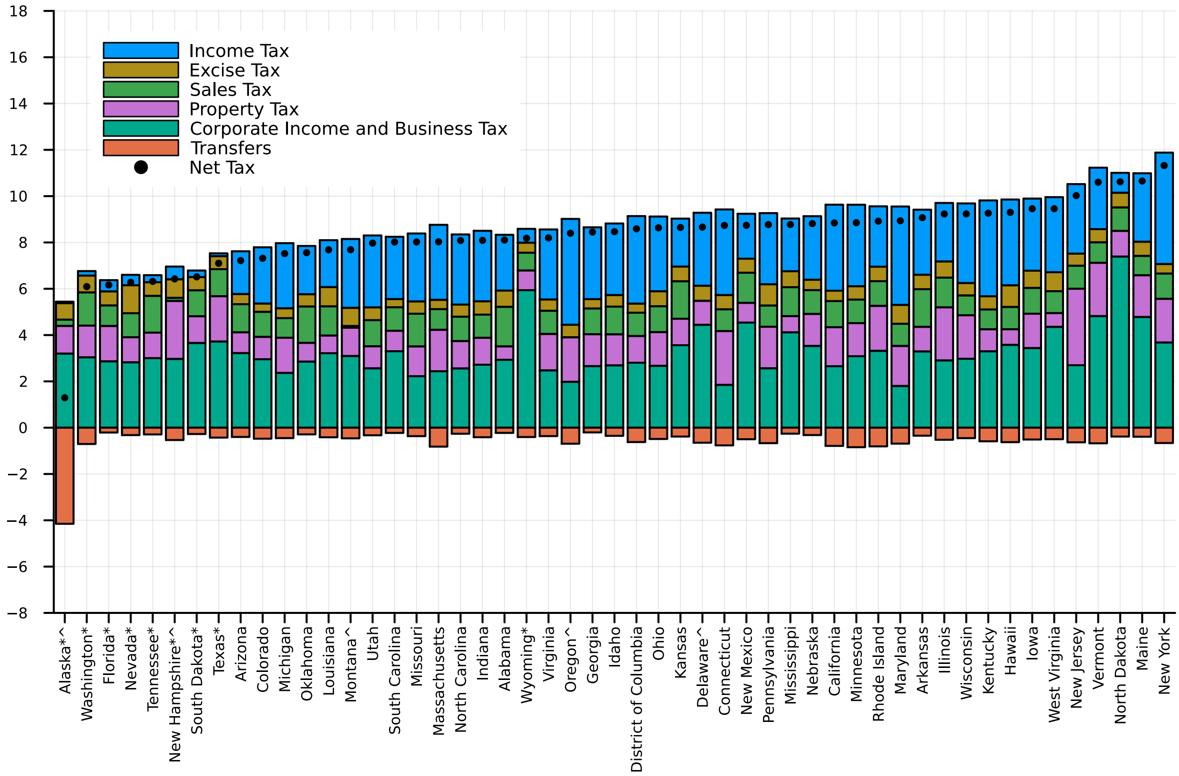

Figure 19: Average tax and transfer rates by state, in percentages, in our working-age sample, 2015/2016. A $*$ superscript denotes states without state income tax, and a $\wedge$ superscript denotes states without state sales tax. Transfers are the state transfers described in Table 4. Computed after re-weighting households as described in Section 4.1. State estate taxes are small and are not broken out separately, but they are included in "Net Tax".

resource rich states such as North Dakota and Wyoming while corporate income taxes are a much smaller source in all states.

Finally, 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 to a small value.[43] 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.

4.2.1 California versus Texas

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

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

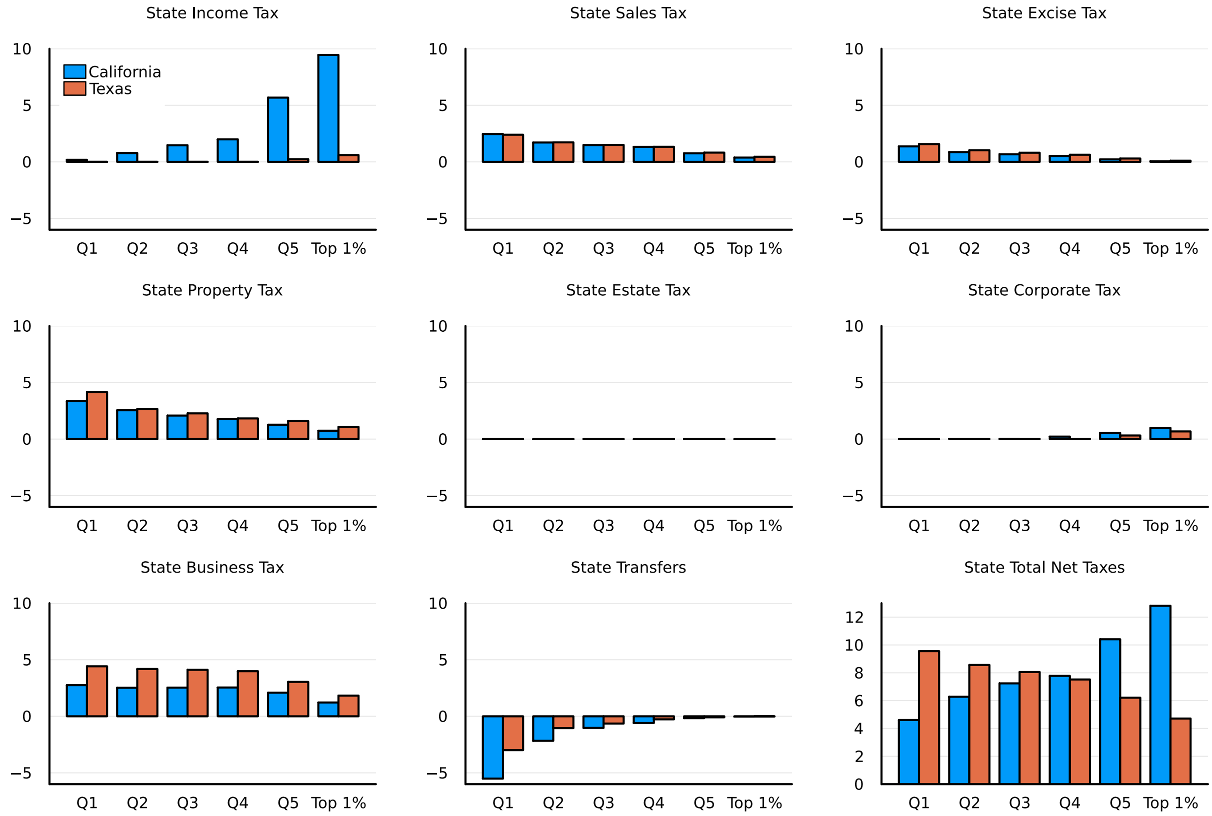

Figure 20: Average tax and transfer rates for California and Texas in our ASEC sample, 2015/2016. The plot shows state and local taxes paid and transfers received across five quintiles of the state pre-government household income distribution and for the top one percent (after re-weighting as described in Section 4.1).

Figure 20 plots taxes paid, as a share of household income, for each quintile of the (reweighted) state household 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.[44] Conversely, property taxes (middle left) are slightly higher in Texas for all incomes.

Neither state collects estate taxes (center panel) but state corporate income taxes are higher in California than in Texas because California had a corporate income tax rate of 8.84 percent in 2015 and 2016, while Texas had no corporate income taxes.[45] In contrast, business taxes are notably higher in Texas.

Transfers (bottom middle) are much larger in California than Texas, especially at the bottom of

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

[45]We attribute small positive state corporate income taxes to Texas households because we assume that corporate income taxes levied in other states are partially born by firm owners in Texas.

the household income distribution. Two factors account for this difference. First, California has 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 20 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 21 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 slightly lower in California for the top one percent 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. Federal transfers at the bottom are larger in California than in Texas. An important factor here is that California spends more state money on Medicaid than Texas and therefore also receives more federal matching dollars. In summary, the combined federal and state tax rate is about twice as low (negative) in California for the lowest incomes and about six percentage points higher for the highest incomes.

4.3 State Level Progressivity

Figure 22 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.[46]

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

[46]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.

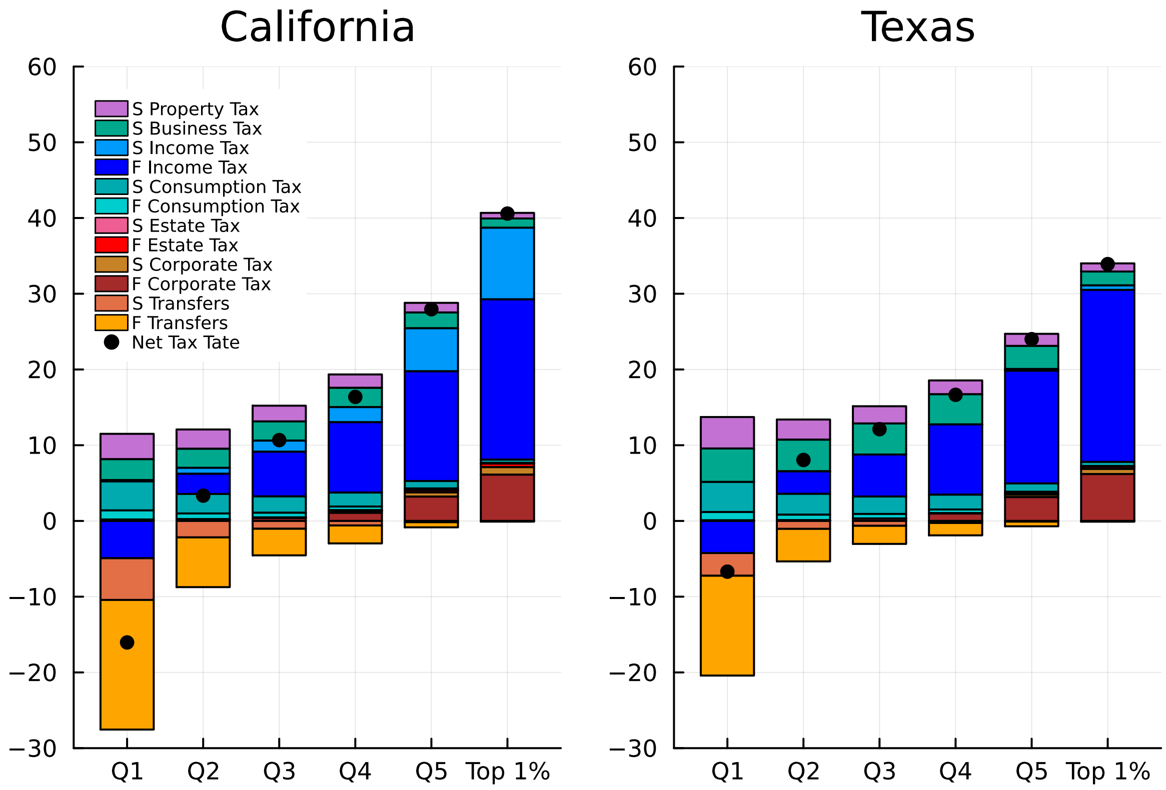

Figure 21: Average state and local as well as federal tax and transfer rates for working-age households in California and Texas, 2015/2016. The plot shows state and local (S) as well as federal (F) taxes paid and transfers received across five quintiles of the state pre-government household income distribution and for the top one percent (after re-weighting as described in Section 4.1).

strongly to progressivity in Alaska thanks to the Alaska Permanent Fund Dividend, which pushes Alaska to the top of our progressivity ranking.

State income taxes contribute positively to progressivity in all states, but the progressivity of those taxes varies across states, and is near zero in the states that do not levy state income taxes. 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 18. 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 one of 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.[47]

[47] Figure O1 in Appendix O.1 plots contributions to progressivity from each tax separately for each state and compares them with the national averages.

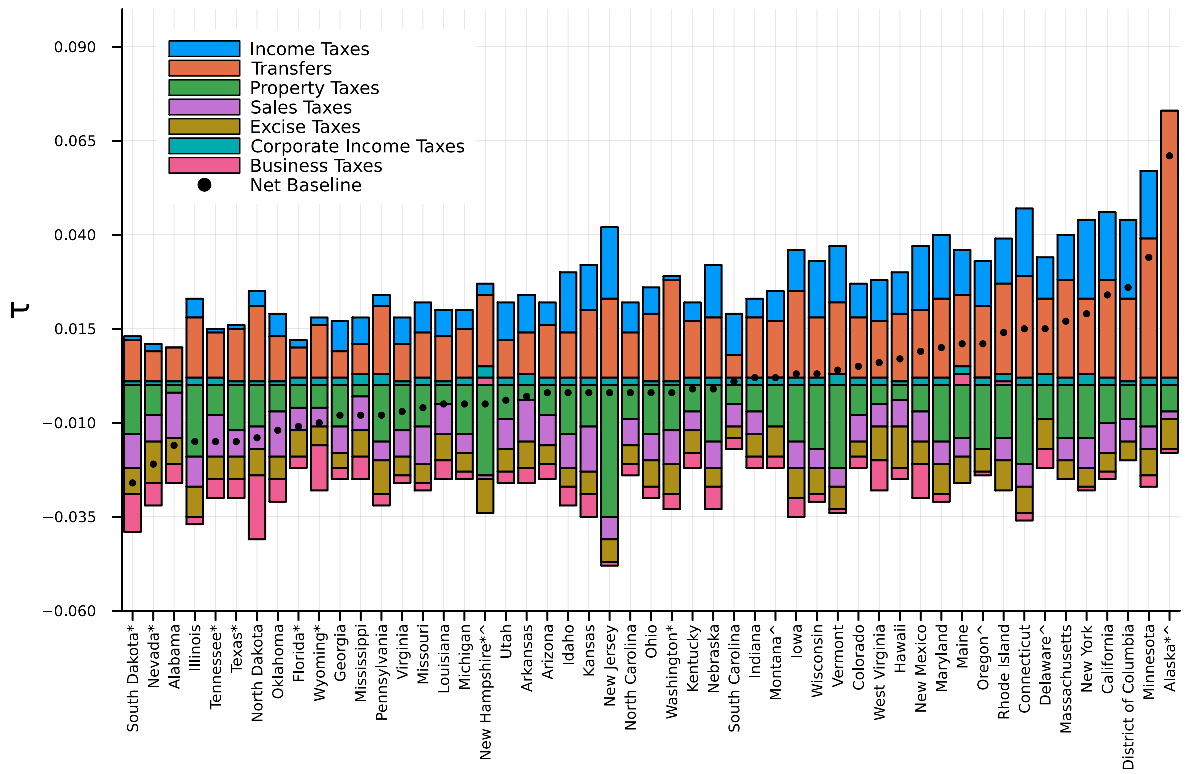

Figure 22: State progressivity decomposition. The plot shows estimates for progressivity induced by each of the state level taxes and transfers indicated in the legend, considering one tax at a time, using household weights constructed as described in Section 4.1. The black dots report overall state baseline progressivity, τ_s. Estimates are for 2015/2016. Estate taxes are small and not shown but included in "Net".

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.[48]

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 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 Q 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

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

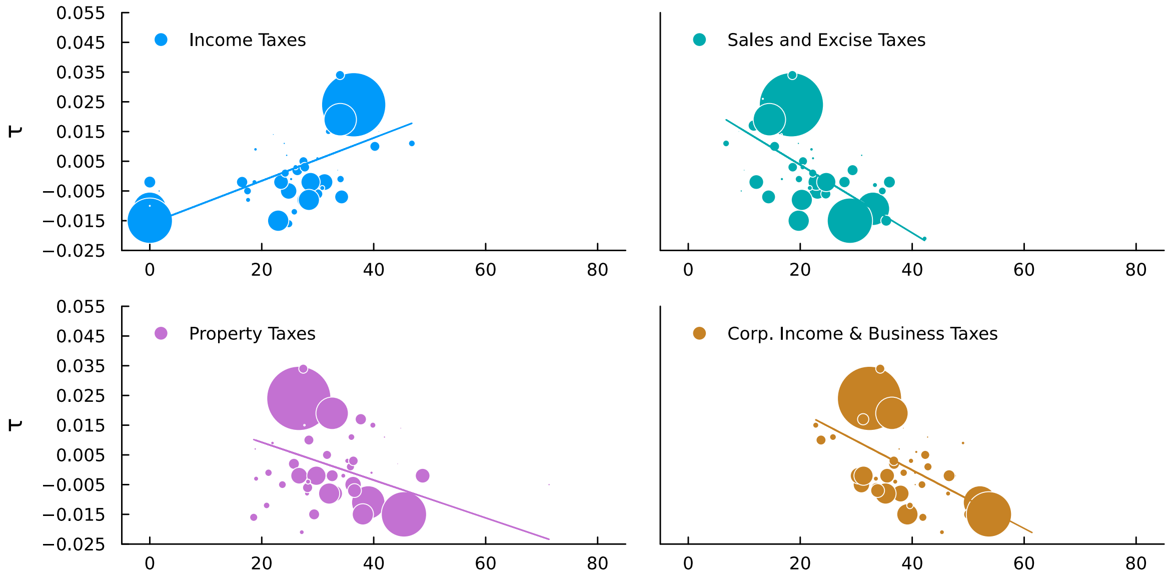

Figure 23: Estimated state tax progressivity τ_s and tax revenue shares. Each bubble represents a state (Alaska is excluded). Bubble size is proportional to state population. Baseline taxes are income, sales, excise & property taxes, and corporate income and business taxes. Revenue data are from the CSLG. Refers to 2015/2016. Lines are the least squares best fits when states are weighted by population. The R^2 values are 0.48, 0.34, 0.12 and 0.34.

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.

4.4 State Progressivity Correlates

Figure 23 illustrates that states that rely more on income taxes tend to have more progressive overall tax and transfer systems. The opposite is true for states that rely more on sales and excise taxes, property taxes, and corporate income and business taxes. This pattern should not come as a surprise given our earlier evidence that income taxes are typically progressive, while sales, property and business taxes are inherently regressive.

Figure 24 plots average state net tax rates (Figure 19) against our state-level estimates of progressivity (Figure 22). There is a positive correlation: states with a higher net tax burden tend to have more progressive taxes. Illinois, New Jersey and North Dakota are the main exceptions to this pattern, which reflects their heavy reliance on regressive property taxes and business taxes (for North Dakota). 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.[49] 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.

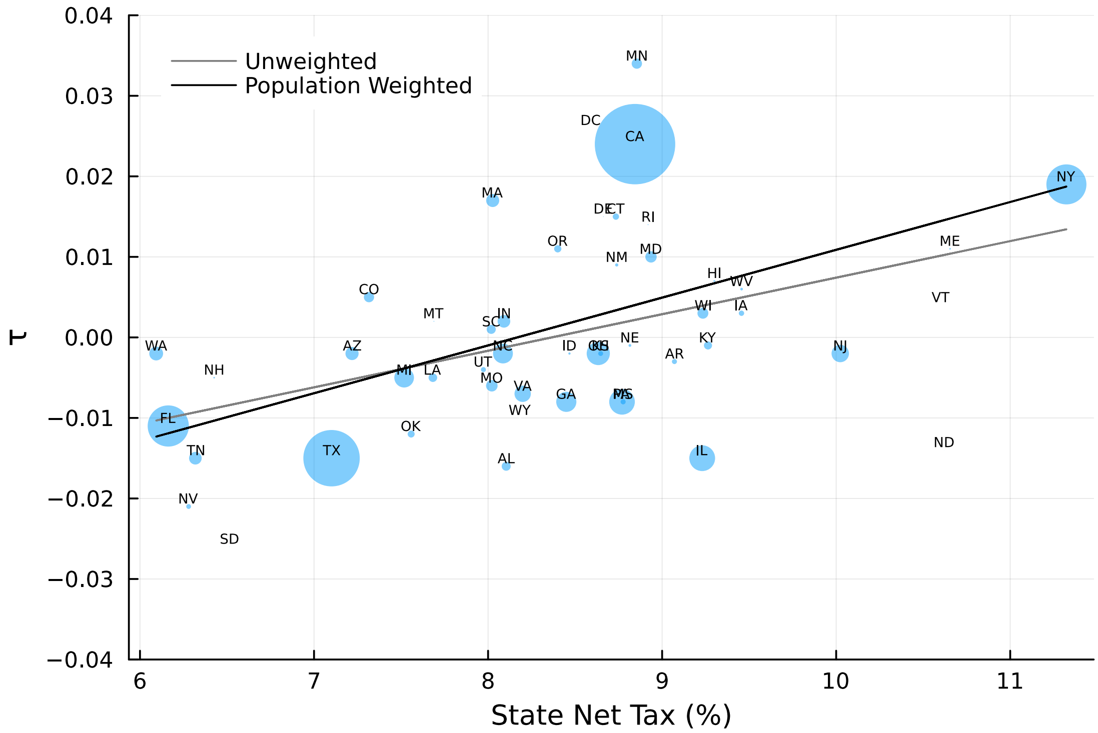

Figure 24: Comparison of state average net tax rates and estimated state tax progressivity τ_s. Excludes Alaska. Dot size is proportional to state population. Estimates for 2015/2016. The gray line is the least squares best fit when states are weighted equally. The black line is the best fit when states are weighted by population. The R^2 values are 0.19 and 0.30.

Of course, this raises the question of why some states have a state income tax, while others 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.[50]

Figure 25 plots the geography of our τ_s estimates, with more progressive states colored in darker shades. Regressive states are concentrated in the South, while states in the West, Midwest and Northeast tend to have more progressive taxes and transfers. One driver of this pat-

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

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

tern 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.

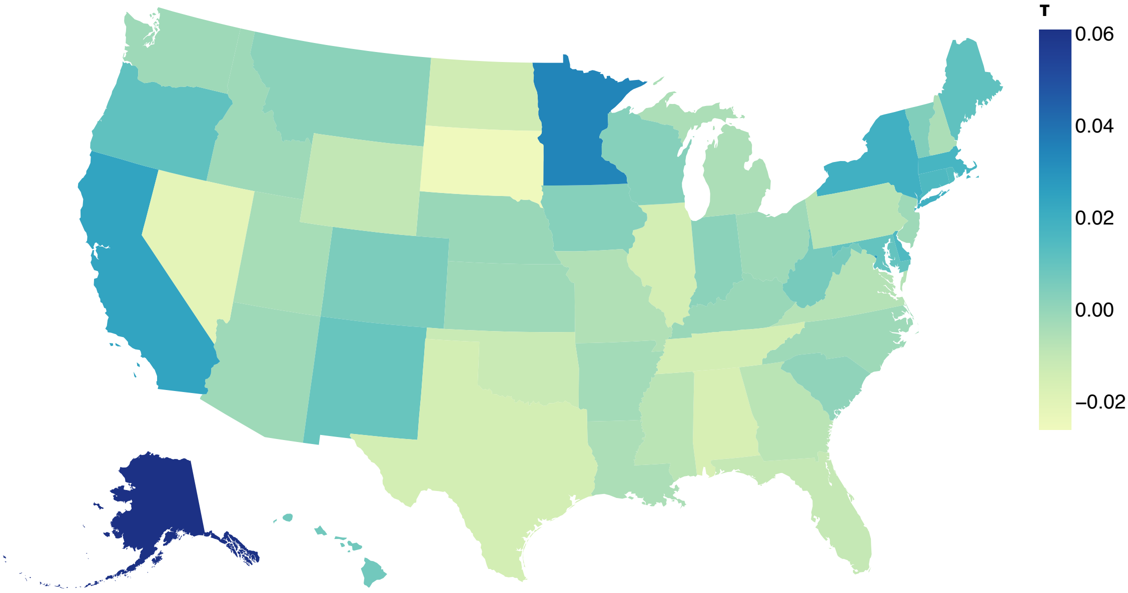

Figure 25: Overall state-level progressivity estimates, τ_s, as reported in section 4.3. Estimates refer to 2015/2016. See notes to Figure 22.

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 26 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.[51] 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

[51] 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.

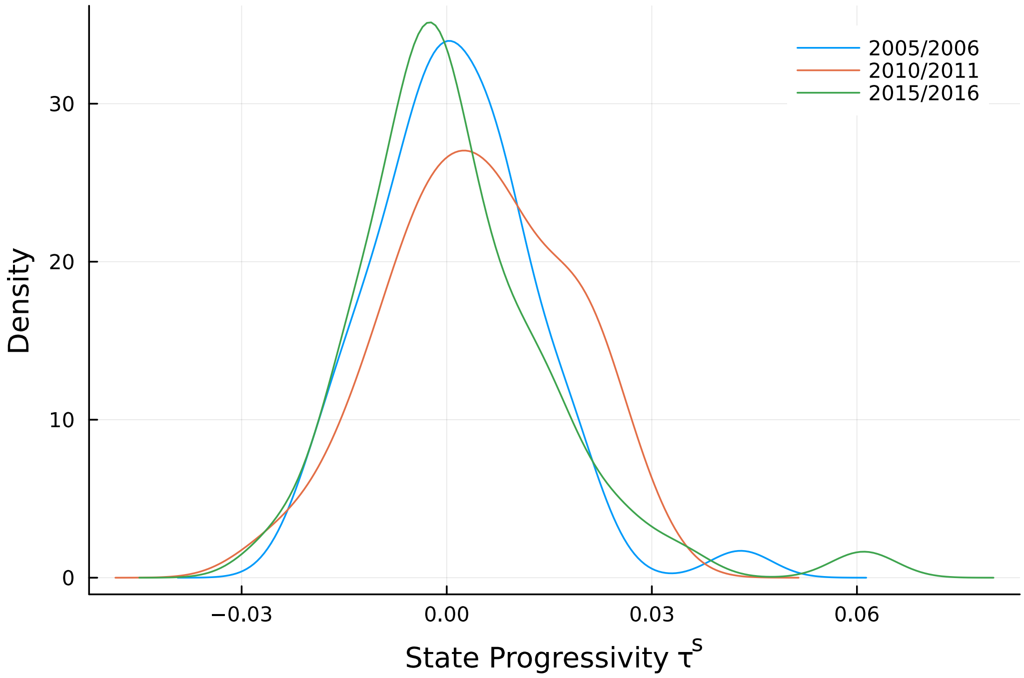

Figure 26: Kernel density estimate of state progressivity, τ_s. Estimates use all state taxes and transfers discussed in Section 4.3.

substantially, thanks to the Affordable Care Act.[52] 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 26 relative to the blue and red ones. See Appendix O.2 for more results and details, including a breakdown of the time variation in each state tax and transfer component.

5 Extension: Spending on Public Goods and Services

In this section, we expand our measure of transfers by including federal, state and local spending on publicly-provided goods and services. We present these calculations as an extension, rather than as part of our baseline, because precisely modeling how public spending on each different budget item is valued by different households is a monumental task beyond the scope of this paper.[53]

[52]The Affordable Care Act (ACA) was signed into law in 2010 but most of its provisions started from 2014. Figure M2 in Appendix M.6 shows more information on how the ACA affected Medicaid enrollment.

[53]There are at least two sources of bias which pull in opposite directions. 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 benefits all

5.1 Methodology

We assess the value of government consumption to households based on its production costs, but we follow different imputation strategies for different components. Appendix P contains a detailed description of our methodology. Here, we summarize the key steps.

We collect data on federal spending from the National Income and Product Accounts (NIPA) and from the Historical Tables of the Office of Management and Budget. Data on state and local spending come from the CSLG.

We split spending into four major categories: health, education, pure public goods (e.g. national defense and public safety), and publicly-provided private goods (e.g., utilities, recreation and culture). To avoid double counting, we subtract from health expenditures all Medicare and Medicaid transfers, as well as premium tax credits and cost-sharing reductions (which account for over 90% of total spending on medical care). For consistency, in this broad measure of transfers, we value Medicaid and Medicare receipt to enrollees at 100 percent of the amount spent. For the other three spending categories, we subtract government revenues from charges that federal, state and local government obtain in exchange of providing such services (e.g., utilities charges, airport fees, highway tolls, etc.).

We take the view that health care as well as publicly-provided private goods and services are a substitute for market goods, so we allocate spending on this category lump-sum to all households.[54] We impute education spending in proportion to the number of children (age 18 or younger) in the household. We allocate spending on pure public goods proportionately to household consumption expenditures. If households had common Cobb-Douglas preferences over these goods and market goods, the socially optimal provision of public goods would imply such an allocation.

5.2 Results

A Broader Measure of Transfer Rates Figure 27 plots average federal and state spending rates, as shares of income, by income decile, together with the baseline transfer rates. At the bottom decile, this additional spending adds nearly 100 percent of income, at the median decile it adds about 30 percent, and at the top decile about 8 percent. Overall, our measure of federal and state spending accounts for 15 percent of aggregate household income. About 4 percent

households, not just those with school-age children. In this case, counting spending as a transfer may underestimate its true value to households.

[54]Federal health care spending for veterans is sizable, so we isolate this component and we attribute it equally to those who declare to be war veterans in ASEC.

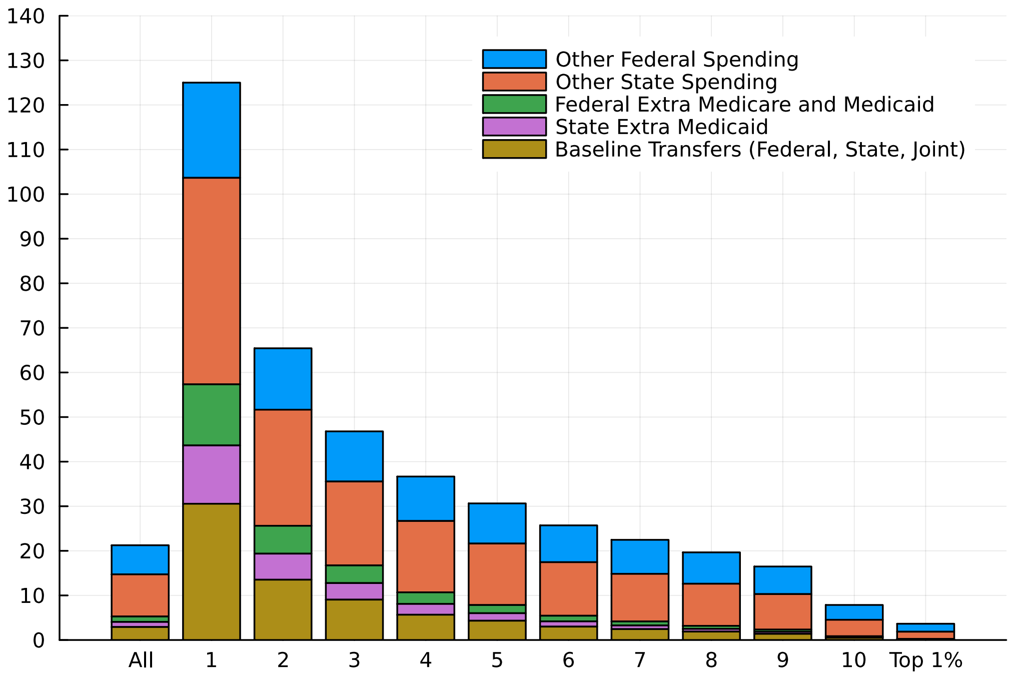

Figure 27: Average transfer rates (as a share of income) for working-age households in 2015/2016. "Other Spending" refers to the federal and state spending categories listed in Appendix P. "Extra Medicare and Medicaid" (for the federal government) and "Extra Medicaid" (for the state governments) is the difference between total government spending on Medicare and Medicaid, and the private values included in baseline transfers (82 and 40 percent of spending, respectively). See notes to Figure 8.

comes from federal spending and about 11 percent from state spending. While the state share falls with income much more sharply than the federal one, it remains larger than the federal share across the entire distribution. Federal spending mostly reflects national defense, while state spending is dominated by education.

A Broader Measure of Fiscal Progressivity Table 6 reports progressivity estimates which include our augmented measure of transfers. Moving to this broad transfer measure has a strong positive impact on progressivity, as expected given the nature of the imputation. Overall progressivity, including all federal and state taxes and transfers, is now 0.283, compared to our baseline estimate of 0.161. The biggest impact of this extension is on state progressivity, where the estimated τ increases from 0.001 (essentially a proportional system) to 0.117. The key contributor to this additional progressivity is state spending on education.

State Heterogeneity Figure 28 shows the effect of this extension on our estimates for state average net tax rates. Net tax rates fall substantially in all states and become negative in most of them. The unweighted average drops from roughly 8 to -2 percent. Adding this extra spending

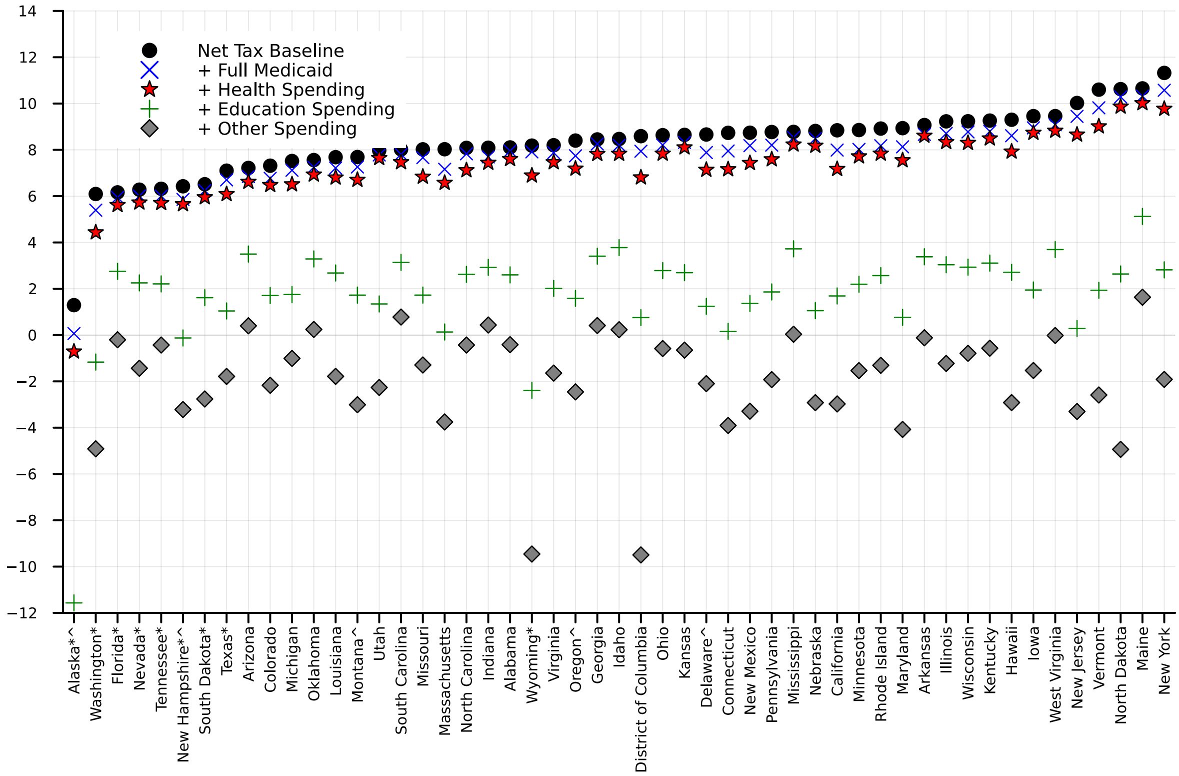

Figure 28: Average tax and transfer rates by state in 2015/2016. Baseline includes state and local income, excise, sales, property, estate, corporate income and business taxes, and the same transfers as in Section 4.3. The other two rates add Medicaid valued at full cost (instead of private values) and all state spending on public goods and services. See notes to Figure 19. The "+ Other Spending" value for Alaska is -21.1 and not shown.

also changes the state ranking significantly because this extra spending is not strongly correlated with net tax rates.[55]

Estimates of state progressivity τ_s for the baseline specification (see also Figure 22) and for this extension are shown in Figure 29. The broad transfer measure boosts progressivity in all states, and our τ estimates become uniformly positive. The component with the largest impact in all states (except for D.C.) is education. Yet, there are strong cross-state differences in the magnitudes of these increases, even excluding outliers such as Alaska and D.C. For instance, the estimated progressivity increases from -0.01 to 0.07 in Florida, and from 0.01 to 0.16 in Maryland. This is because state public spending per capita does not correlate too closely with our baseline estimates of state tax progressivity. For example, as shown by Figure P1 in Appendix P.1, 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 progressivity estimates. As a result, the progressivity ranking across states changes substantially. Some states—for example,

[55] As illustrated by Figure M3 in Appendix M.6 and Figure P1 in Appendix P.1.

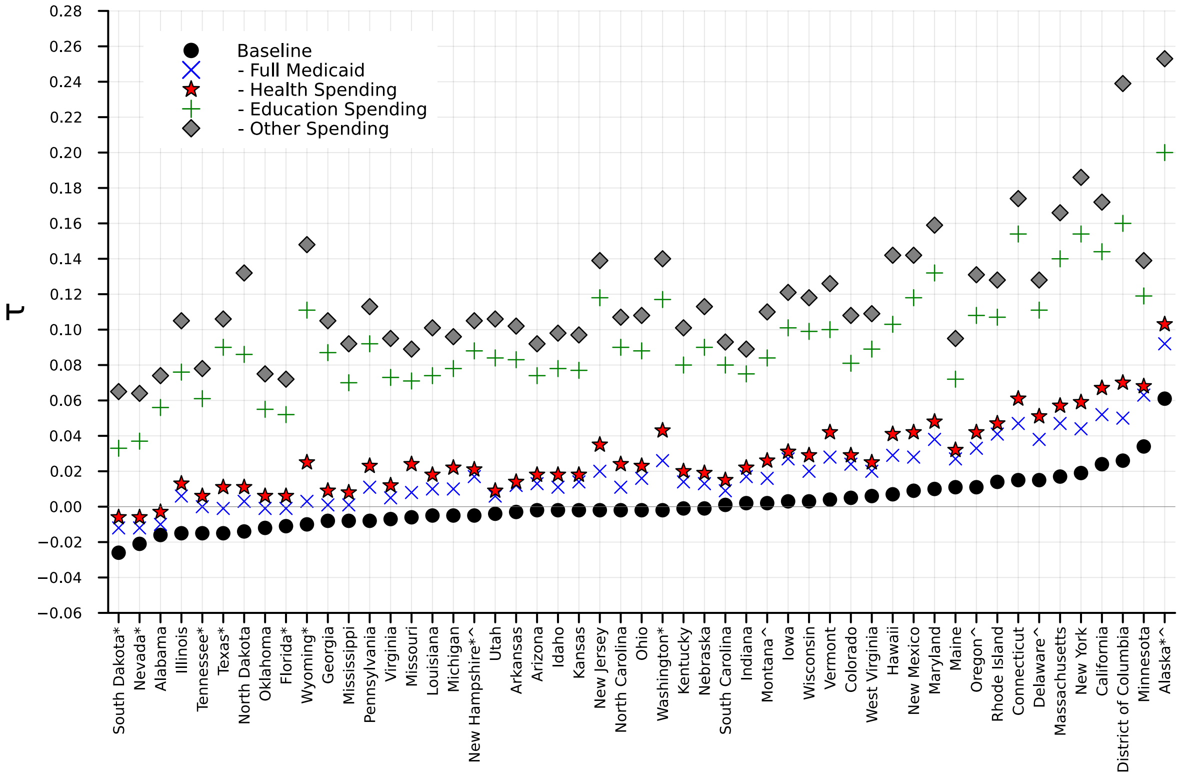

Figure 29: State progressivity. Baseline includes state and local income, excise, sales, property, estate, corporate income and business taxes taxes, and the same transfers as in Section 4.3. The additional results consider as extra transfers the full cost of Medicaid and state-level spending on public goods and services, broken down by education, health and other. See notes to Figure 22. ASEC sample, 2015/2016.

Minnesota—fall to a lower position, while others— for example, Wyoming—jump upward in the ranks.

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, and ensuring consistency with aggregate measures and state-level policies, 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, property and business 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.

The state-level 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)?

Another set of important questions concerns the implications of differences in tax rates and tax progressivity for economic outcomes 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. There is also substantial interest in understanding how differences in state progressivity influence migration decisions. For example, Moretti and Wilson (2017) investigate the importance of top marginal state income tax rates on the location decisions of star scientists. In this regard, while the standard Tiebout model suggests that differences in the provision of local public goods are a key driver of migration decisions, there are few papers studying the role of local tax progressivity differences. Our findings also relate to the extent of income insurance provided by federal versus state fiscal policies. Could it be that individuals in high-progressivity states are exposed to larger fluctuations in their before tax and transfer incomes? We hope our measurements will prove useful for researchers working on these and other questions.

Finally, recent U.S. fiscal policy, namely the One Big Beautiful Bill Act, is going to reduce federal funding for several federal and joint federal-state transfer programs, such as SNAP and Medicaid. These changes are expected to increase cross-state progressivity heterogeneity even further, as some of the current high-progressivity states, including California and New York, have vowed to compensate for lost federal funding using their own resources, while some low-progressivity states such as Texas and Alabama have not indicated any intention to do so.

References

AKCIGIT, U., J. GRIGSBY, T. NICHOLAS, AND S. STANTCHEVA (2022): "Taxation and Innovation in the Twentieth Century," *Quarterly Journal of Economics*, 137(1), 329–385.

ALTIG, D., A. AUERBACH, P. HIGGINS, D. KOEHLER, L. KOTLIKOFF, E. TERRY, AND V. YE (2020): "Did the 2017 Tax Reform Discriminate against Blue State Voters?," *National Tax Journal*, 73(4), 1087–1108.

AUTEN, G., AND D. SPLINTER (2024): "Income Inequality in the United States: Using Tax Data to Measure Long-Term Trends," *Journal of Political Economy*, 132(7), 2179–2227.

BAHL, R., J. MARTINEZ-VAZQUEZ, AND S. WALLACE (2002): "State and Local Government Choices in Fiscal Redistribution," *National Tax Journal*, 55(4), 723–742.

BAKER, S. (2024): "Property Tax Pass-Through to Renters: A Quasi-experimental Approach," Working Paper.

BAKER, S. R., P. JANAS, AND L. KUENG (2020): "Correlation in State and Local Tax Changes," Working Paper 20-115, Swiss Finance Institute.

BAKER, S. R., S. JOHNSON, AND L. KUENG (2021): "Shopping for Lower Sales Tax Rates," *American Economic Journal: Macroeconomics*, 13(3), 209–250.

BARGAIN, O., M. DOLLS, H. IMMERVOLL, D. NEUMANN, A. PEICHL, N. PESTEL, AND S. SIEGLOCH (2015): "Tax Policy and Income Inequality in the United States, 1979-2007," *Economic Inquiry*, 53(2), 1061–1085.

BEE, A., B. D. MEYER, AND J. X. SULLIVAN (2013): "The Validity of Consumption Data: Are the Consumer Expenditure Interview and Diary Surveys Informative?," in *Improving the Measurement of Consumer Expenditures*, edited by C.D. Carroll, T.F. Crossley, and J. Sabelhaus, pp. 204–240. University of Chicago Press.

BENABOU, R. (2002): "Tax and Education Policy in a Heterogeneous-Agent Economy: What Levels of Redistribution Maximize Growth and Efficiency?," *Econometrica*, 70(2), 481–517.

BERMAN, M., AND R. REAMEY (2016): "Permanent Fund Dividends and Poverty in Alaska," Working paper, Institute of Social and Economic Research, University of Alaska Anchorage.

BOAR, C., AND V. MIDRIGAN (2022): "Efficient Redistribution," *Journal of Monetary Economics*, 131, 78–91.

BORELLA, M., M. D. NARDI, M. PAK, N. RUSSO, AND F. YANG (2023): "The Importance of Modeling Income Taxes over Time: U.S. Reforms and Outcomes," *Journal of the European Economic Association*, 21(6), 2237–2286.

CHERNICK, H. (2005): "On the Determinants of Subnational Tax Progressivity in the U.S.," *National Tax Journal*, 58(1), 93–112.

CHODOROW-REICH, G. (2019): "Geographic Cross-Sectional Fiscal Spending Multipliers: What Have We Learned?," *AEJ: Policy*, 11, 1–34.

COOPER, D. H., B. F. LUTZ, AND M. G. PALUMBO (2015): "The Role of Taxes in Mitigating Income Inequality across the U.S. States," *National Tax Journal*, 68(4), 943–974.

COUNCIL OF STATE GOVERNMENTS (2016): "The Book of States," volume 48.

DAVIS, M. A., W. D. LARSON, S. D. OLINER, AND J. SHUI (2021): "The Price of Residential

Land for Counties, ZIP Codes, and Census Tracts in the United States," *Journal of Monetary Economics*, 118, 413–431.

DAVIS, T., D. KNOEPFLE, S. T. SUN, AND C. YANNELIS (2018): "Greener on the Other Side: Estimating Consumer Sensitivity to Local Sales Tax Changes," Working Paper.

DOBRIDGE, C., P. KENNEDY, P. LANDEFELD, AND J. MORTENSON (2023): "The TCJA and Domestic Corporate Tax Rates," Finance and Economics Discussion Series 2023-078, Board of Governors of the Federal Reserve System.

DOBRIDGE, C., P. LANDEFELD, AND J. MORTENSON (2021): "Corporate Taxes and the Earnings Distribution: Effects of the Domestic Production Activities Deduction," Finance and Economics Discussion Series 2021-081, Board of Governors of the Federal Reserve System.

ERNST & YOUNG (2016): "Total State and Local Business Taxes: State-by-State Estimates for Fiscal Year 2015," Report.

FAJGELBAUM, P. D., E. MORALES, J. C. S. SERRATO, AND O. ZIDAR (2019): "State Taxes and Spatial Misallocation," *Review of Economic Studies*, 86(1), 333–376.

FELDSTEIN, M. S. (1969): "The Effects of Taxation on Risk Taking," *Journal of Political Economy*, 77(5), 755–764.

FERRIERE, A., P. GRÜBENER, G. NAVARRO, AND O. VARDISHVILI (2023): "On the Optimal Design of Transfers and Income-Tax Progressivity," *Journal of Political Economy Macroeconomics*, 1(2), 276–333.

FINKELSTEIN, A., N. HENDREN, AND E. F. P. LUTTMER (2019): "The Value of Medicaid: Interpreting Results from the Oregon Health Insurance Experiment," *Journal of Political Economy*, 127(6), 2836–2874.

FINKELSTEIN, A., AND R. MCKNIGHT (2008): "What Did Medicare Do? The Initial Impact of Medicare on Mortality and Out of Pocket Medical Spending," *Journal of Public Economics*, 92(7), 1644–1668.

FLECK, J. (2024): "Imputing Medicaid Transfers at the State Level," Working Paper.

FLECK, J., AND C. SIMPSON-BELL (2019): "Public Insurance in Heterogeneous Fiscal Federations: Evidence from American Households," Meeting Paper 296, Society for Economic Dynamics.

FLOOD, S., M. KING, R. RODGERS, S. RUGGLES, J. R. WARREN, D. BACKMAN, A. CHEN, G. COOPER, S. RICHARDS, M. SCHOUWEILER, AND M. WESTBERRY. (2023): *IPUMS CPS: Version 11.0 Dataset*.

GALE, W. G., S. JOSHI, C. PULLIAM, AND J. SABELHAUS (2022): "Taxing business incomes: Evidence from the Survey of Consumer Finances," Discussion paper, Brookings Institution.

GARNER, T. I., G. JANINI, L. PASZKIEWICZ, AND M. VENDEMIA (2006): "The CE and the PCE: a comparison," *Monthly Labor Review*, 129, 20–46.

GRAVELLE, J. (2007): "Who Pays Property Taxes? A Look at the Excise Tax Effects of Property Taxes across the States," *Proceedings: Annual Conference on Taxation and Minutes of the Annual Meeting of the National Tax Association*, 100, 94—97.

GUNER, N., R. KAYGUSUZ, AND G. VENTURA (2014): "Income Taxation of U.S. Households:

Facts and Parametric Estimates," *Review of Economic Dynamics*, 17(4), 559–581.

HABIB, B. (2018): "How CBO Adjusts for Survey Underreporting of Transfer Income in Its Distributional Analyses," Working Paper 2018-07, Congressional Budget Office.

HASSLER, J., J. V. RODRIGUEZ MORA, K. STORESLETTEN, AND F. ZILIBOTTI (2005): "A Positive Theory of Geographic Mobility and Social Insurance," *International Economic Review*, 46(1), 263–303.

HEATHCOTE, J., K. STORESLETTEN, AND G. L. VIOLANTE (2017): "Optimal Tax Progressivity: An Analytical Framework," *Quarterly Journal of Economics*, 132(4), 1693–1754.

——— (2020): "How Should Tax Progressivity Respond to Rising Income Inequality?," *Journal of the European Economic Association*, 18(6), 2715–2754.

HENDREN, N., AND B. SPRUNG-KEYSER (2020): "A Unified Welfare Analysis of Government Policies," *Quarterly Journal of Economics*, 135(3), 1209–1318.

HOWE, E. T., AND D. J. REEB (1997): "The Historical Evolution of State and Local Tax Systems," *Social Science Quarterly*, 78(1), 109–121.

HOYNES, H. W., AND E. F. LUTTMER (2011): "The insurance value of state tax-and-transfer programs," *Journal of Public Economics*, 95(11), 1466–1484.

IMBODEN, C., J. VOORHEIS, AND C. WEBER (2023): "Self-Employment Income Reporting on Surveys," Working Paper 23-19, U.S. Census Bureau, Center for Economic Studies.

KLINE, P., N. PETKOVA, H. WILLIAMS, AND O. ZIDAR (2019): "Who Profits from Patents? Rent-Sharing at Innovative Firms," *Quarterly Journal of Economics*, 134(3), 1343–1404.

KÖNIG, J. (2023): "Bias in Tax Progresssivity Estimates," *National Tax Journal*, 76(2), 233–473.

KOSAR, G., AND R. A. MOFFITT (2017): "Trends in Cumulative Marginal Tax Rates Facing Low-Income Families, 1997–2007," *Tax Policy and the Economy*, 31(1), 43–70.

LAMADON, T., M. MOGSTAD, AND B. SETZLER (2022): "Imperfect Competition, Compensating Differentials, and Rent Sharing in the US Labor Market," *American Economic Review*, 112(1), 169–212.

LIN, D. (2022): "Methods and Assumptions of the CPS ASEC Tax Model," Social, Economic, and Housing Statistics Division Working Paper 2022-18, Census Bureau.

MAZEROV, M. (2002): "Developing Capacity to Analyze the Distributional Impact of State and Local Taxes," *State Tax Notes February*, 18, 561–590.

MCINTYRE, R. S., R. DENK, N. FRANCIS, M. GARDNER, W. GOMAA, F. HSU, AND R. SIMS (2003): "Who Pays? A Distributional Analysis of the Tax Systems in All 50 States," 2nd edition, The Institute on Taxation and Economic Policy.

MINNESOTA DEPARTMENT OF REVENUE, TAX RESEARCH DIVISION (2024): "2024 Minnesota Tax Incidence Study: An Analysis of Minnesota's Household and Business Taxes," Report.

MORETTI, E., AND D. J. WILSON (2017): "The Effect of State Taxes on the Geographical Location of Top Earners: Evidence from Star Scientists," *American Economic Review*, 107(7), 1858–1903.

OECD (2016): *Fiscal Federalism 2016: Making Decentralisation Work*. OECD Publishing, Paris.

O'HARA, A. (2006): "Tax Variable Imputation in the Current Population Survey," in Selected

Papers Given at the 2006 IRS Research Conference, edited by J. Dalton and B. Kilss, pp. 169-180. Internal Revenue Service.

PADGITT, K. (2009): "Updated State and Local Option Sales Tax," Fiscal Fact 196, Tax Foundation.

PECHMAN, J. A., AND B. A. OKNER (1974): *Who Bears the Tax Burden?* Brookings Institution.

PERSSON, M. (1983): "The Distribution of Abilities and the Progressive Income Tax," *Journal of Public Economics*, 22(1), 73–88.

PIKETTY, T. (1995): "Social Mobility and Redistributive Politics," *Quarterly Journal of Economics*, 110(3), 551–584.

PIKETTY, T., E. SAEZ, AND G. ZUCMAN (2018): "Distributional National Accounts: Methods and Estimates for the United States," *Quarterly Journal of Economics*, 133(2), 553–609.

ROBINSON, S., AND A. TAZHITDINOVA (2023): "What Drives Tax Policy? Political, Institutional and Economic Determinants of State Tax Policy," NBER Working Paper 31268.

ROTHBAUM, J. L. (2015): "Comparing Income Aggregates: How do the CPS and ACS Match the National Income and Product Accounts, 2007-2012," Social, Economic, and Housing Statistics Division Working Paper 2015-01, Census Bureau.

RUGGLES, S., S. FLOOD, M. SOBEK, D. BACKMAN, A. CHEN, G. COOPER, S. RICHARDS, R. RODGERS, AND M. SCHOUWEILER (2024): *IPUMS USA: Version 15.0*.

SAMMARTINO, F., AND N. FRANCIS (2016): "Federal-State Income Tax Progressivity," Report, Tax Policy Center, Urban Institute and Brookings Institution.

SCOTT, C. E., AND R. K. TRIEST (1993): "The Relationship between Federal and State Individual Income Tax Progressivity," *National Tax Journal*, 46(2), 95–108.

SERRATO, J. C. S., AND O. ZIDAR (2016): "Who Benefits from State Corporate Tax Cuts? A Local Labor Markets Approach with Heterogeneous Firms," *American Economic Review*, 106(9), 2582–2624.

SPLINTER, D. (2020): "U.S. Tax Progressivity and Redistribution," *National Tax Journal*, 73(4), 1005–1024.

STANTCHEVA, S. (2021): "Understanding Tax Policy: How Do People Reason?," *Quarterly Journal of Economics*, 136(4), 2309–2369.

SUITS, D. B. (1977): "Measurement of Tax Progressivity," *American Economic Review*, 67(4), 747–752.

TSOODLE, L. J., AND T. M. TURNER (2008): "Property Taxes and Residential Rents," *Real Estate Economics*, 36(1), 63–80.

WEBSTER, B. H. (2011): "Evaluating the Use of the New Current Population Survey's Annual Social and Economic Supplement Questions in the Census Bureau Tax Model," Research report, Census Bureau.

WHEATON, L., AND K. STEVENS (2016): "The Effect of Different Tax Calculators on the Supplemental Poverty Measure," Research report, Urban Institute.

Appendix

The appendix to ”Fiscal Progressivity of the U.S. Federal and State Governments” (Fleck, Heathcote, Storesletten, Violante, September 2025) 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 describes our method for imputing rents to owner-occupiers.
- Section D presents summary statistics from the SOI augmented ASEC dataset and our baseline sample. It also contains additional details on the comparison with Piketty, Saez, and Zucman (2018) and Auten and Splinter (2024).
- Sections E and F contain detailed explanations on the measurement and imputation of federal and state income, sales, and excise taxes
- Section G describes our measurement of property taxes paid by homeowners and renters, and explains why property taxes are regressive.
- Section H compares the imputed state tax revenues for income, consumption, and property taxes to external benchmarks.
- Sections I and J explain the measurement and imputation of federal and state corporate income taxes, and state business taxes, respectively.
- Section K describes our model for imputing estate taxes.
- Section L explains how we incorporate Affordable Care Acts provisions into our federal tax and transfer calculations for 2015-16.
- Section M explains the measurement and imputation of federal and state transfers.
- Section N documents the methodology we use to align state income distributions before estimating state specific tax and transfer progressivity.
- Section O provides additional results on our baseline estimates of state progressivity.
- Section P explains the measurement and imputation of federal and state spending as a household transfer and on how these extended estimates affect the average tax rate and the degree of progressivity.
- Section Q 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.[56] 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.

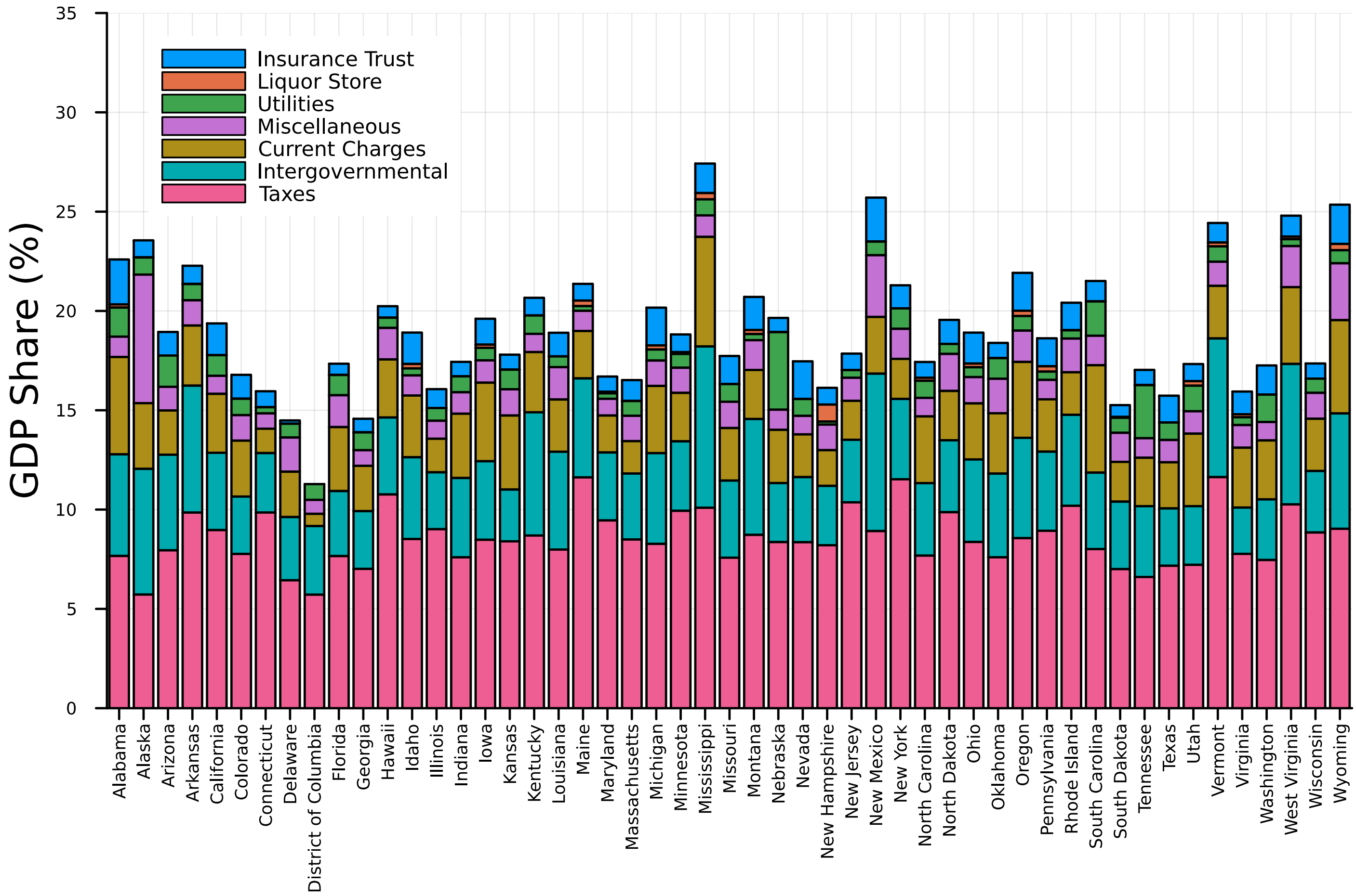

Figure A1: State and Local Total Revenues as Shares of State GDP (2016). Source: Census of State and Local Governments (CSLG) and Bureau of Regional Analysis (BEA).

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).

[56] "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.[57]

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).

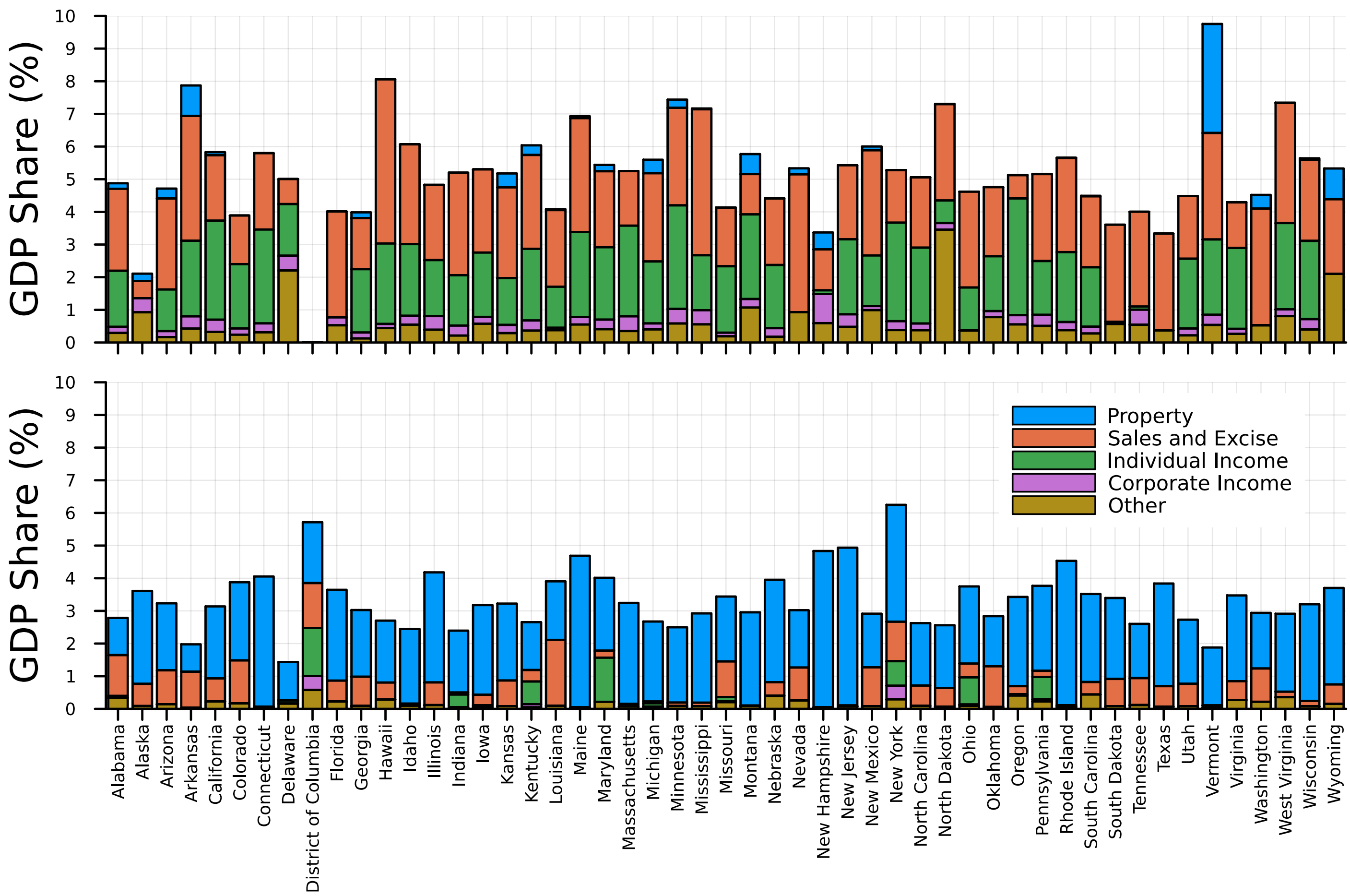

Figure A2: Top Panel: State Tax Revenues as Shares of State GDP (2016). Bottom Panel: Local Tax Revenues as Shares of State GDP (2016). Source: CSLG and BEA.

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 and other

[57]See Appendix E for more details on local income taxes.

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 2.10 and appendix J.

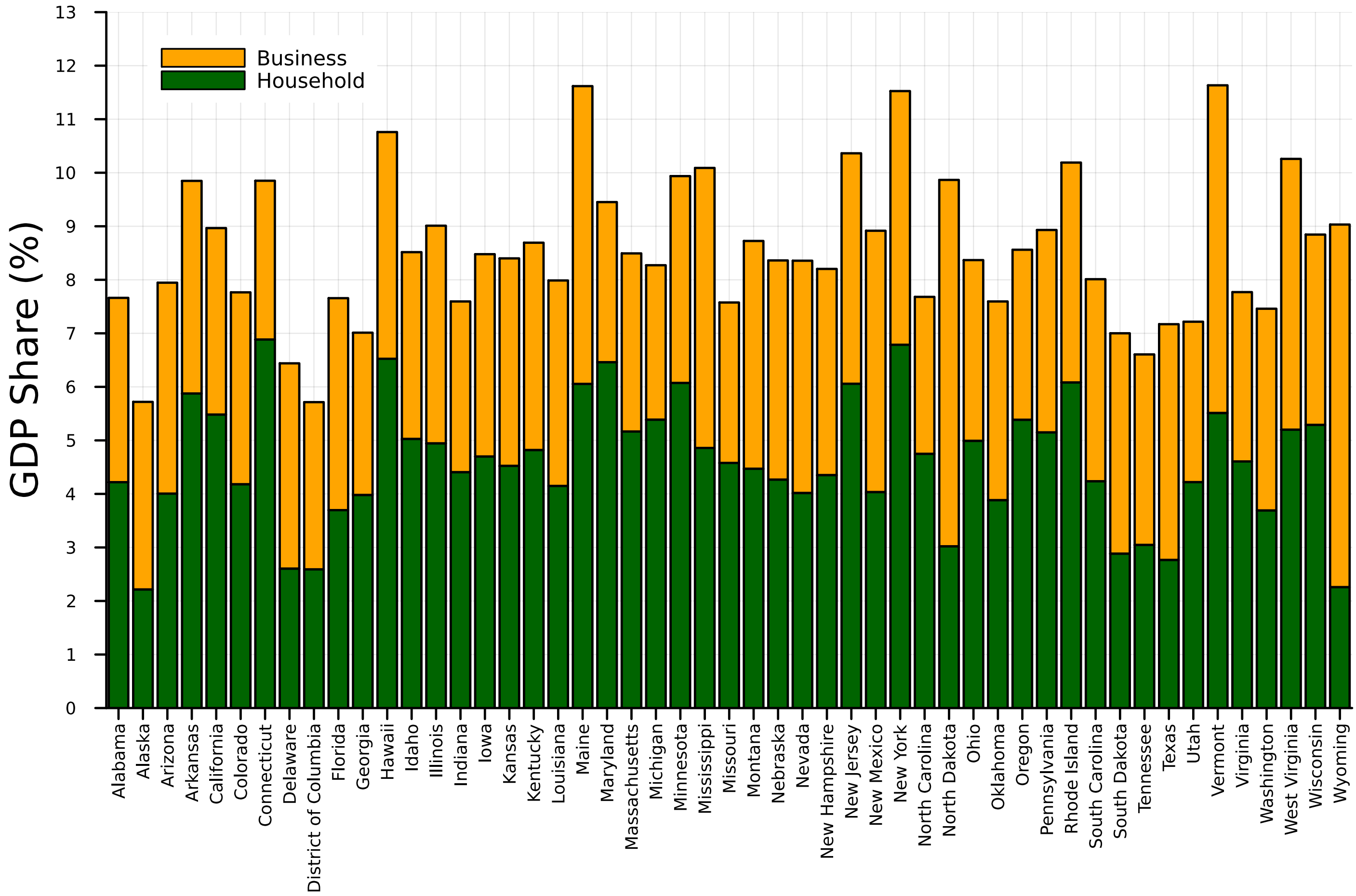

Figure A3: State and Local Total Tax Revenues from Businesses and Households as Shares of State GDP (2016). Source: CSLG, BEA and Ernst & Young (2016).

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).[58] 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. Both of these methods also cap the modified income values at a maximum possible value. 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 the original responses of survey respondents regarding 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

[58] 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.

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,

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

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 $\underline{K} + \overline{K} + \widehat{K} = K$.[59]

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 or by under-reporting or under-sampling of high-income respondents, 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.[60] 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.[61] The SOI data also provide the employee portion of all FICA taxes, and we impute the employer portion as described in section 2.6.

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.[62]

[59] The ASEC IPUMS retirement income variable consists of two components for which replacement thresholds are published. Hence, we consider those components as individual variables when computing the lower bound of total household income, $\underline{y}_i$.

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

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

[62] Note that other than unemployment compensation, the SOI data do not provide any of the transfer categories available in ASEC (see Table 4). Hence, we do not replace transfer variables.

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 greater than or equal to $200,000.
2. At least one of the income tax variables is at the topcode for at least one household member.[63]

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 of choosing the standard deduction. Thus, this income threshold gives us reasonable measures of state and local income taxes as well as property taxes.[64]

For the entire dataset in 2015/2016, the share of SOI replaced households is 5.7 percent. For reference, the share of tax returns with AGI above $200,000 is 4.6 percent.[65] We report the total and by income decile replaced share in the tables in Appendix D.

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.

[63] As mentioned above, income taxes are topcoded only in 2005 and 2006.

[64] 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.

[65] 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).

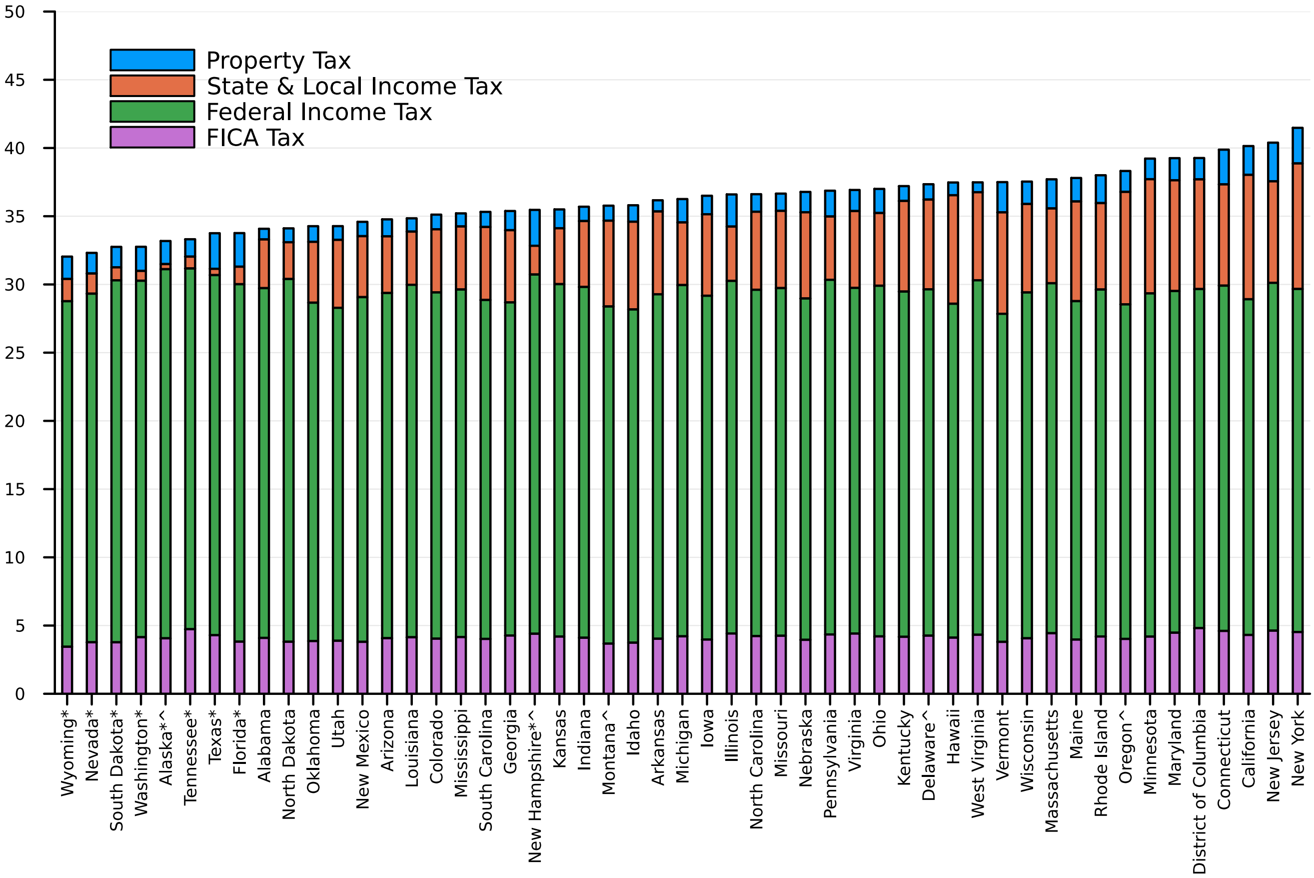

Figure B1: Taxes and transfers as a percentage of adjusted gross income (AGI) for households with AGI between \$500,000 and \$1,000,000 by state. Source: IRS SOI state tables 2016. States without income tax are marked with an asterisk. According to the SOI, households with AGI in this range that reside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

C Owner-Occupied Rents

We estimate an aggregate time series for outstanding mortgage debt relative to monthly payments ratio, which we label M_t/P_t. The FRED series for outstanding mortgage debt is *Households and Nonprofit Organizations; Total Mortgages; Liability, Level* (series HNOTMLQ027S). The series for mortgage payments is *Mortgage Debt Service Payments as a Percent of Disposable Personal Income* (FRED series MDSP) times *Disposable Personal Income* (series DSPI). Note that this mortgage debt service series is from the Federal Reserve Board of Governors Household Debt Service Ratios release, which is based on credit bureau reports, and which again includes escrow payments. See https://www.federalreserve.gov/releases for more details.

Appendix G details our nearest-neighbor matching procedure which allows us to use the ACS to impute to our ASEC households estimate for home value $V_{i,t}$ and for monthly mortgage payments $P_{i,t}$. Note that the ACS measure of mortgage payments includes escrow for property taxes and insurance.

Let $Z_{i,t}$ denote the Zillow rent to price ratio for household i's county in year t. See Appendix G for more details on these ratios.

We estimate the depreciation rate for housing as the ratio between *Net fixed investment: Residential: Consumption of fixed capital* (FRED series A754RC1A027NBEA) and *Household and Nonprofit Organizations: Real Estate at Market Value* (series HNOREMV). The implied depreciation rate δ_t for 2016 is 1.71%, which is close to the value of 1.41% estimated by Davis and Heathcote (2005).

For each ASEC household we proceed as follows:

1. Nearest neighbor match to ACS $\Rightarrow$ estimated household home value $V_{i,t}$ and estimated household monthly mortgage payment $P_{i,t}$
2. Household home equity estimate is $E_{i,t} = V_{i,t} - \frac{M_t}{P_t} P_{i,t}$
3. Owner-occupied rent estimate is $OOR_{i,t} = (Z_{i,t} - \delta_t) E_{i,t}$

D Household Data: Summary Statistics

D.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 D1 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).

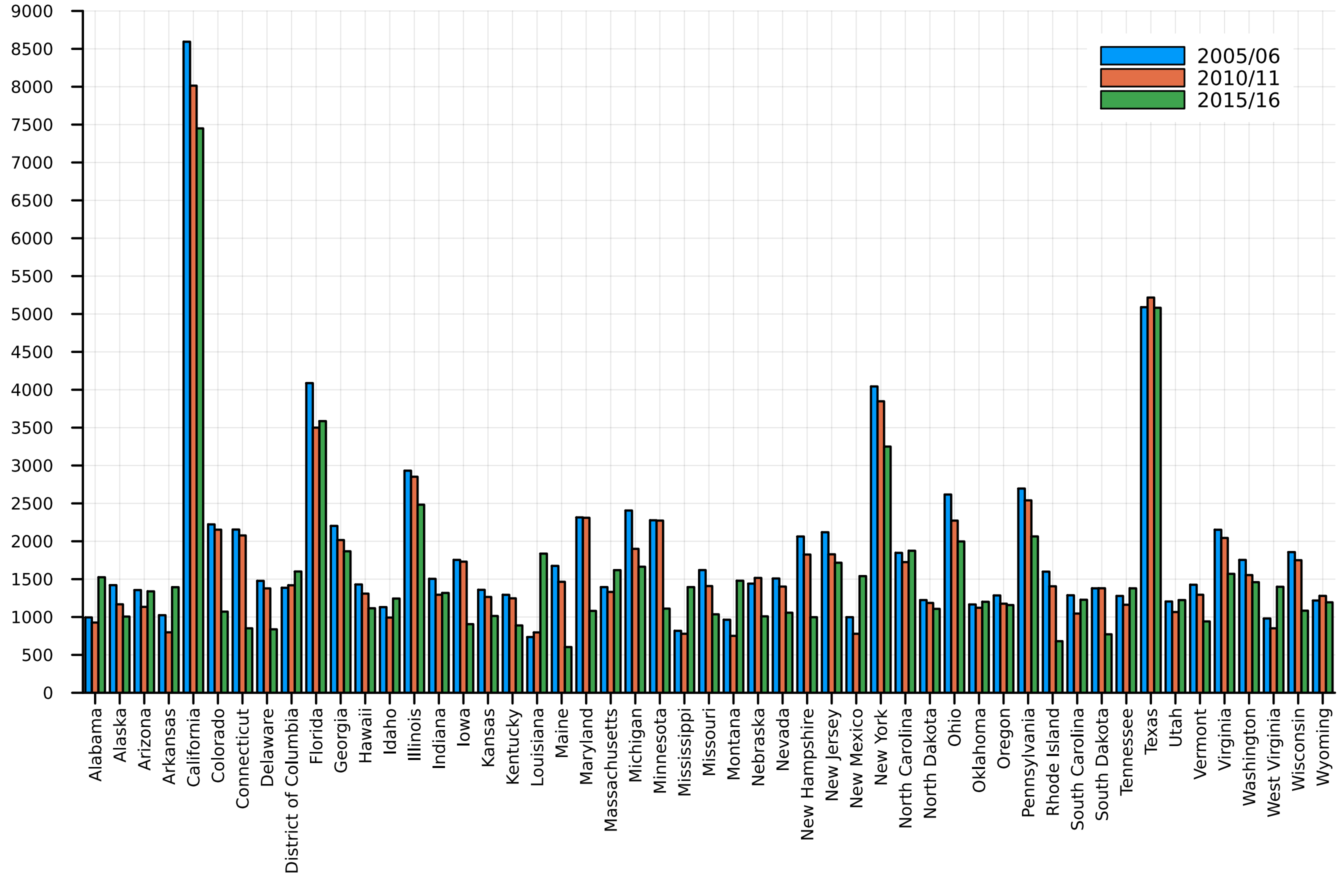

Figure D1: Households by state in the ASEC baseline sample. This sample selects households with heads aged between 25 and 60 and one spouse having at least part-time minimum-wage labor earnings.

D.2 ASEC Sample

	All	1	2	3	4	5	6	7	8	9	10	Top 1%
Household Income (NIPA consistent)	170,639	30,632	51,604	68,734	85,944	105,174	126,688	152,317	185,817	239,913	659,367	2,519,652
Wage and Salary Income (NIPA consistent)	113,868	24,302	41,358	54,975	70,146	85,894	103,446	124,519	150,219	185,869	297,921	855,840
Business and Farm Income (NIPA consistent)	14,622	428	1,334	2,012	2,888	4,492	6,004	7,734	11,625	22,289	87,404	154,786
Asset and Residual Income (NIPA consistent)	26,840	229	548	1,152	1,651	2,520	3,292	4,776	6,693	11,257	236,141	1,412,917
Owner Occupied Rent (ASEC+)	6,689	1,791	3,716	5,384	5,273	5,536	6,293	6,624	7,201	8,445	16,626	44,769
Taxes on Production and Imports (ASEC+)	8,619	3,882	4,649	5,211	5,986	6,733	7,652	8,664	10,078	12,054	21,274	51,341
<= 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	84	100
Household Income (ASEC)	106,497	20,470	35,156	47,158	60,453	74,715	90,368	109,644	133,540	169,530	323,892	779,044
Household Income (ASEC+)	123,716	20,477	35,182	47,232	60,532	74,877	90,599	109,964	134,227	171,263	492,648	2,067,059
Total Transfers	4,976	9,360	6,980	6,223	4,873	4,551	3,807	3,717	3,506	3,328	3,419	3,428
Federal Transfers	3,370	6,156	4,596	4,142	3,170	3,071	2,527	2,618	2,515	2,364	2,541	2,587
School Lunch (ASEC, self-reported)	130	347	237	160	135	100	84	71	61	53	50	65
Veterans' Benefits (ASEC, self-reported)	258	205	175	247	249	293	263	345	272	254	276	418
Survivors' Benefits (ASEC, self-reported)	185	142	101	137	110	132	145	287	307	191	303	183
Disability Benefits (ASEC, self-reported)	215	256	226	221	192	222	205	162	196	218	249	109
SS SI and DI Benefits (recipients age < 62; ASEC, self-reported)	478	813	779	748	470	485	417	340	287	242	203	75
SS OA Benefits (recipients age >= 62; ASEC, self-reported)	422	342	385	481	435	435	344	372	460	446	516	699
SNAP (CBO imputed)	401	1,656	839	538	343	220	146	96	70	61	37	33
SSI (CBO imputed)	205	525	358	332	210	167	119	102	72	83	85	124
Housing Assistance (CBO imputed)	109	754	182	67	36	16	20	6	2	2	2	4
Medicare (imputed, cash value)	666	855	941	797	673	703	551	538	513	509	585	666
ACA Cost Sharing Reductions (imputed)	83	99	244	202	143	81	37	15	7	5	0	0
Pell Grants (ASEC self-reported, imputed)	218	162	129	211	174	219	197	284	270	299	235	211
State Transfers	281	420	337	350	294	275	268	247	204	231	188	101
Unemployment Insurance (ASEC, self-reported)	187	304	222	223	198	169	161	157	141	161	135	73
Workers' Compensation (ASEC, self-reported)	83	109	107	117	86	95	93	77	51	59	39	13
Alaska PFD (ASEC, self-reported, imputed)	11	7	9	9	10	11	13	13	12	12	13	16
Joint Federal-State Transfers	1,325	2,784	2,046	1,732	1,409	1,205	1,013	852	787	733	690	739
TANF (ASEC, self-reported)	31	113	35	30	20	23	22	17	23	12	13	28
Medicaid (imputed, cash value)	1,294	2,672	2,011	1,701	1,389	1,182	991	835	764	722	677	711
Amount cond. on recipiency	3,053	4,050	3,779	3,629	3,164	2,884	2,573	2,395	2,278	2,186	2,043	1,858
Recipients (% of persons)	30	68	54	44	35	29	24	19	17	16	15	18
Income Taxes (imputed, ASEC, SOI, CSLG, BEA)	23,005	-2,237	335	2,738	4,933	7,580	10,852	16,212	24,106	31,472	134,013	686,094
Federal (ASEC, SOI)	18,299	-2,363	-278	1,687	3,474	5,606	8,386	12,877	20,242	25,822	107,496	548,817
Earned Income Tax Credit	-510	-2,177	-1,279	-622	-371	-234	-162	-108	-71	-46	-25	-40
Child Tax Credit	-384	-40	-214	-378	-533	-627	-681	-687	-434	-174	-70	-12
State & Local (ASEC, SOI, CSLG, BEA)	4,706	126	613	1,051	1,458	1,974	2,467	3,335	3,864	5,651	26,517	137,277
FICA (employee, employer, self-employment; ASEC, SOI, imputed)	12,437	2,884	4,930	6,560	8,381	10,304	12,433	14,989	17,960	21,685	24,245	41,914
ACA Premium Tax Credit (imputed)	-185	-241	-546	-492	-325	-145	-54	-24	-15	-8	0	0
ACA Shared Responsibility Payment (imputed)	33	31	37	34	29	31	29	26	31	33	47	70
Estate Taxes (imputed)	268	32	32	31	32	34	56	125	135	230	1,974	11,879
Federal	211	25	25	25	25	26	45	99	107	180	1,548	9,216
State	58	7	7	6	7	7	11	26	28	50	426	2,662
Consumption Taxes (imputed, CEX, BEA, CSLG)	3,542	1,922	2,236	2,495	2,787	3,104	3,420	3,799	4,242	4,735	6,681	14,001
Federal (excise and customs)	746	437	509	559	617	677	737	806	872	951	1,297	2,487
State (sales and excise)	2,796	1,485	1,727	1,936	2,170	2,427	2,683	2,993	3,370	3,784	5,384	11,514
Sales	1,840	864	1,014	1,159	1,331	1,511	1,703	1,944	2,256	2,614	4,006	9,417
Excise	956	621	714	777	840	916	979	1,049	1,114	1,170	1,378	2,097
Property Taxes (imputed, ACS, SOI)	2,722	1,309	1,559	1,721	1,850	1,996	2,199	2,434	2,707	3,269	8,175	20,421
Owners	3,290	1,618	1,871	1,950	2,039	2,197	2,380	2,595	2,866	3,477	8,621	21,189
Renters	1,721	1,210	1,348	1,451	1,574	1,622	1,760	1,912	2,064	2,242	5,726	14,954
Corporate Income Taxes (imputed)	3,988	14	36	100	95	197	878	1,807	2,536	3,879	30,316	180,016
Federal (all profits + all labor)	3,398	11	31	85	81	155	760	1,559	2,157	3,232	25,891	154,373
State (all profits + in-state labor)	590	2	5	15	15	42	117	248	378	647	4,425	25,643
State Business Taxes (imputed, ASEC, CEX, BEA, EY)	4,454	1,044	1,607	2,049	2,560	3,061	3,718	4,413	5,427	6,943	13,712	35,499
Labor	3,073	674	1,145	1,518	1,940	2,320	2,844	3,388	4,110	4,989	7,801	22,523
Consumers	650	347	393	433	482	523	586	649	757	872	1,458	4,211
Landowners	731	24	69	99	139	218	288	377	559	1,082	4,453	8,765
Public Spending (imputed, BEA, CSLG)	27,261	20,728	20,544	20,663	22,324	23,972	25,673	27,884	30,607	33,948	46,264	86,311
Federal (all households)	11,138	6,540	7,108	7,730	8,570	9,471	10,462	11,625	13,065	14,852	21,954	44,994
State (in-state households)	16,123	14,188	13,437	12,933	13,754	14,502	15,211	16,259	17,543	19,096	24,310	41,317
Joint Filers (ASEC, %)	58	27	35	41	48	56	64	71	75	79	82	84
HH Head Filers (ASEC, %)	11	30	20	15	13	10	8	6	5	4	3	3
Single Filers (ASEC, %)	31	43	45	44	39	34	28	23	20	17	15	12
HH owners (ASEC, %)	64	24	40	54	59	65	71	76	80	83	85	88
HH size (ASEC)	2.9	2.5	2.5	2.6	2.7	2.8	3	3	3.1	3.2	3.3	3.4
HH head age (ASEC)	43.7	41.1	42.5	43.1	43.1	43.6	43.5	44.2	44.5	45.3	46.5	46.8
HH head age > 60 (ASEC, %)	2	2	2	3	2	2	2	3	2	3	3	4
HH at least one member age > 65 (ASEC, %)	3	3	3	3	3	3	3	3	3	4	4	5
N, unweighted	40,158	4,084	3,992	3,961	3,980	4,026	4,026	4,060	4,078	4,004	3,944	389
N, ASEC weights	68,651,070	6,864,913	6,864,522	6,865,291	6,865,087	6,865,676	6,864,803	6,864,880	6,864,951	6,865,130	6,865,642	688,344

Table D1: 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 SOI data.

D.3 Full ASEC Dataset

	All	1	2	3	4	5	6	7	8	9	10	Top 1%
Household Income (NIPA consistent)	124,271	3,615	14,955	30,829	48,368	67,115	88,090	114,062	147,675	199,432	528,450	1,999,077
Wage and Salary Income (NIPA consistent)	76,956	254	3,355	14,514	30,853	46,465	65,087	85,548	113,653	152,785	257,030	726,206
Business and Farm Income (NIPA consistent)	10,559	-146	96	461	1,161	1,849	3,061	5,591	8,015	13,957	71,539	133,088
Asset and Residual Income (NIPA consistent)	23,022	190	1,880	4,902	6,227	7,195	7,732	9,338	10,839	14,633	167,186	1,060,846
Owner Occupied Rent (ASEC+)	7,108	981	7,529	7,856	6,039	6,740	6,408	6,669	6,891	7,677	14,291	35,252
Taxes on Production and Imports (ASEC+)	6,626	2,336	2,095	3,095	4,089	4,866	5,803	6,916	8,278	10,379	18,404	43,685
<= 0 (%)	0	1	0	0	0	0	0	0	0	0	0	0
SOI Replaced (%)	6	0	0	0	0	0	0	0	0	0	57	100
Household Income (ASEC)	76,439	337	4,522	16,615	31,543	45,507	61,698	80,792	105,953	142,955	274,450	692,056
Household Income (ASEC+)	88,348	341	4,553	16,714	31,693	45,736	62,034	81,252	106,670	144,433	389,947	1,626,442
Total Transfers	14,442	26,564	27,660	21,483	15,710	12,754	10,188	8,863	7,553	6,686	6,960	6,453
Federal Transfers	12,658	22,931	25,401	19,361	13,589	10,912	8,641	7,518	6,435	5,710	6,082	5,614
School Lunch (ASEC, self-reported)	99	105	101	161	161	123	100	78	63	52	44	60
Veterans' Benefits (ASEC, self-reported)	458	732	787	582	391	360	380	371	400	293	289	424
Survivors' Benefits (ASEC, self-reported)	403	475	718	577	374	317	235	306	313	359	352	341
Disability Benefits (ASEC, self-reported)	289	518	465	295	257	247	232	249	204	204	216	102
SS SI and DI Benefits (recipients age < 62; ASEC, self-reported)	772	1,897	1,501	912	822	715	518	475	370	288	222	134
SS OA Benefits (recipients age >= 62; ASEC, self-reported)	5,211	7,011	11,198	8,862	5,898	4,619	3,718	3,139	2,663	2,367	2,636	2,456
SNAP (CBO imputed)	533	1,437	1,000	985	722	479	292	182	110	73	52	56
SSI (CBO imputed)	435	1,787	726	461	378	311	222	174	107	95	86	96
Housing Assistance (CBO imputed)	296	1,968	389	324	151	61	28	17	8	2	13	19
Medicare (imputed, cash value)	3,890	6,811	8,336	5,959	4,058	3,284	2,602	2,283	1,931	1,698	1,941	1,669
ACA Cost Sharing Reductions (imputed)	70	2	6	87	219	189	119	54	17	6	2	0
Pell Grants (ASEC self-reported, imputed)	202	186	175	157	159	207	195	190	248	273	230	257
State Transfers	253	242	278	221	314	293	271	264	242	221	183	95
Unemployment Insurance (ASEC, self-reported)	153	86	135	153	187	189	171	162	157	159	130	66
Workers' Compensation (ASEC, self-reported)	91	153	138	62	118	95	90	91	74	50	42	19
Alaska PFD (ASEC, self-reported, imputed)	9	3	5	5	8	9	10	11	12	11	11	9
Joint Federal-State Transfers	1,531	3,391	1,981	1,901	1,807	1,549	1,276	1,080	876	755	695	744
TANF (ASEC, self-reported)	49	184	84	62	40	27	20	23	19	19	11	19
Medicaid (imputed, cash value)	1,482	3,207	1,896	1,839	1,767	1,523	1,256	1,057	857	737	684	725
Amount cond. on recipiency	3,812	5,876	5,023	4,307	3,977	3,764	3,277	2,934	2,583	2,362	2,267	2,044
Recipients (% of persons)	32	61	45	50	48	40	32	25	20	16	15	18
Income Taxes (imputed, ASEC, SOI, CSLG, BEA)	16,076	15	-359	-641	881	3,243	5,919	9,255	15,659	26,293	100,465	530,443
Federal (ASEC, SOI)	12,835	15	-361	-784	361	2,285	4,438	7,153	12,503	21,980	80,734	425,724
Earned Income Tax Credit	-353	-29	-389	-982	-916	-510	-296	-193	-113	-70	-36	-30
Child Tax Credit	-226	-1	-1	-18	-121	-260	-410	-515	-558	-292	-85	-18
State & Local (ASEC, SOI, CSLG, BEA)	3,241	1	2	142	520	958	1,481	2,102	3,157	4,313	19,732	104,719
FICA (employee, employer, self-employment; ASEC, SOI, imputed)	8,452	30	399	1,729	3,682	5,552	7,792	10,308	13,719	18,144	23,161	37,751
ACA Premium Tax Credit (imputed)	-160	-5	-15	-216	-495	-458	-273	-92	-28	-12	-2	0
ACA Shared Responsibility Payment (imputed)	27	15	9	21	32	30	29	29	28	32	42	59
Estate Taxes (imputed)	192	33	32	32	32	32	33	36	117	139	1,438	9,368
Federal	152	26	25	26	25	25	26	28	92	110	1,135	7,380
State	41	7	7	6	7	7	7	8	25	30	304	1,988
Consumption Taxes (imputed, CEX, BEA, CSLG)	2,928	1,227	1,372	1,801	2,160	2,464	2,821	3,240	3,729	4,393	6,068	12,168
Federal (excise and customs)	626	290	318	411	493	552	623	701	794	896	1,187	2,205
State (sales and excise)	2,301	938	1,055	1,390	1,667	1,911	2,198	2,538	2,934	3,497	4,880	9,963
Sales	1,482	533	594	804	973	1,139	1,347	1,598	1,897	2,366	3,565	8,030
Excise	819	405	461	586	695	773	851	941	1,038	1,131	1,316	1,933
Property Taxes (imputed, ACS, SOI)	2,377	1,132	1,620	1,651	1,676	1,802	1,917	2,121	2,395	2,854	6,601	17,543
Owners	2,872	1,381	1,787	2,000	2,017	2,042	2,120	2,312	2,561	3,015	6,955	18,312
Renters	1,518	1,070	1,216	1,213	1,314	1,451	1,557	1,674	1,864	2,132	4,573	12,887
Corporate Income Taxes (imputed)	2,987	13	105	212	244	335	446	681	1,974	3,196	22,644	142,528
Federal (all profits + all labor)	2,544	11	89	180	208	285	378	568	1,706	2,716	19,282	122,382
State (all profits + in-state labor)	443	2	16	31	36	50	68	112	268	480	3,361	20,146
State Business Taxes (imputed, ASEC, CEX, BEA, EY)	3,144	253	367	756	1,292	1,812	2,421	3,176	4,106	5,596	11,657	29,691
Labor	2,078	7	93	403	853	1,290	1,789	2,351	3,083	4,142	6,770	18,935
Consumers	539	246	267	329	380	429	485	552	636	790	1,275	3,441
Landowners	527	0	7	25	59	93	147	273	387	664	3,613	7,315
Public Spending (imputed, BEA, CSLG)	21,441	11,138	11,478	14,998	17,511	18,535	20,693	23,099	26,005	30,188	40,760	75,613
Federal (all households)	9,247	4,386	4,866	5,986	6,819	7,567	8,575	9,802	11,326	13,519	19,619	39,640
State (in-state households)	12,194	6,752	6,612	9,012	10,693	10,968	12,118	13,297	14,679	16,669	21,140	35,974
Joint Filers (ASEC, %)	44	2	14	28	35	40	48	58	67	74	79	81
HH Head Filers (ASEC, %)	8	3	8	13	14	11	10	7	5	4	3	4
Single Filers (ASEC, %)	31	11	31	42	45	44	39	33	26	21	17	14
HH owners (ASEC, %)	63	20	71	56	52	59	64	70	76	82	85	86
HH size (ASEC)	2.5	1.6	1.8	2.1	2.3	2.4	2.6	2.8	2.9	3	3.1	3.3
HH head age (ASEC)	51.2	58.2	61.6	54.6	49.7	48.5	47.5	47.3	47.3	47.9	49.5	49.2
HH head age > 60 (ASEC, %)	32	52	63	46	32	27	23	20	19	17	20	18
HH at least one member age > 65 (ASEC, %)	27	44	57	42	27	22	18	16	14	13	15	14
N, unweighted	69,720	6,754	6,511	6,766	6,984	6,962	7,050	7,076	7,268	7,237	7,114	690
N, ASEC weights	126,293,396	12,629,194	12,629,224	12,628,946	12,629,598	12,629,312	12,628,997	12,629,262	12,629,944	12,629,092	12,629,593	1,263,209

Table D2: 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 SOI data.

D.4 Other Estimates of the Net Tax Rate Distribution

This section contains more details on how we compare our estimates of net tax rates to those presented by two leading articles on the progressivity of the U.S. federal tax and transfer system, Piketty, Saez, and Zucman (2018) and Auten and Splinter (2024).

D.4.1 Comparison to Piketty, Saez, and Zucman (2018)

For our detailed comparison with Piketty, Saez, and Zucman (2018), PSZ thereafter, we have obtained the micro data underlying their analysis from `https://gabriel-zucman.eu/usdina/`. The dataset is constructed by combining tax, surveys and national account data. We impose a sample selection that is as consistent as possible with ours. Notably, we use tax units (better proxy for households than individuals), we select the age range 20-64 (age in their data is in only reported classes 20-44, 45-64, 65+) for the primary filer, and impose the same income threshold as in our baseline sample, i.e. we keep in the sample tax units with at least one member whose income is above $7,250. We define income as national factor income (PSZ income = fainc + govin + npinc), the closest definition to ours. Among taxes, we include federal and state income taxes, payrol taxes, sales and excise taxes, corporate and business taxes, estate taxes net of the EITC (PSZ taxes = ditaf + ditas + govcontrib + salestax + corptax + proprestax + propbustax + estatetax - eitc). Among transfers we include Social security income, DI, UI, SNAP, Supplemental security income, Veterans' benefits, Workers' compensation, TANF, Other cash benefits, Pell grants, and Medicare and Medicaid valued at full cost (PSZ transfers = ssincoa + ssincdi + uiinc + difoo + disup + divet + diwco + tanfinc + othben + pell + medicare + medicaid). These definitions of taxes and transfers correspond closely to ours.

D.4.2 Comparison to Auten and Splinter (2024)

AS use a range of (internal) confidential administrative data from IRS, including 1040 tax returns and third-party-reported on labor income (W-2), capital income, and social security income. Their definition of pre-tax national income is very similar to ours. David Splinter kindly provided statistics on income, taxes, and transfers by income decile and for the top 1 pct based on a sample with primary-filer ages between 25 and 60, as in our sample selection. Since their sample includes all individuals with non-negative incomes, we do the same in our sample selection used for this comparison. In addition, they construct households and split these into individuals. Individuals are then sorted based on their equivalized household income (dividing income by the square root of the number of individuals per household). When comparing our results to theirs, we do the same equivalization at the household level in our ASEC+ sample. The results are documented in Figure 13.

E 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).[66] 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.[67]

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

[66] 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.

[67] 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).

F 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) household furnishings and equipment; (9) apparel and services; (10) vehicle purchases (net outlay); (11) gasoline and motor oil; (12) other vehicle expenses (excluding insurance); (13) public and other transportation; (14) entertainment; (15) personal care products and services; (16) reading; (17) tobacco; (18) insurance;[68] (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 taxes are lumped together in category 21 ("Other"). We also impute total expenditure on goods and services, labeled category 22.

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

$$c_{jt}^{IMP}(y) \equiv \frac{C_{jt}^{BEA}}{C_{jt}^{CEX}} \cdot c_{jt}^{CEX}(y), \tag{F1}$$

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 F1 reports the adjustment factors $C_{jt}^{BEA}/C_{jt}^{CEX}$ for 2016.[69] Column (22) refers to total expenditure on goods and services.

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

[69] 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(22)
2005	1.472	1.366	1.749	0.580	1.057	1.169	1.379	1.191	1.324	0.687	1.075	1.405	1.508	1.072	3.520	6.014	2.163	0.594	1.512
2006	1.469	1.398	1.532	0.590	0.996	1.147	1.343	1.278	1.334	0.655	1.083	1.435	1.386	1.123	3.416	6.423	2.167	0.597	1.504
2010	1.489	1.567	1.937	0.614	1.058	1.174	1.359	1.215	1.384	0.708	1.175	1.349	1.504	1.218	3.625	6.515	2.309	0.541	1.638
2011	1.469	1.580	1.772	0.624	1.090	1.152	1.447	1.242	1.447	0.748	1.151	1.431	1.629	1.210	3.398	5.464	2.349	0.556	1.637
2015	1.502	1.594	1.763	0.554	1.171	1.133	1.397	1.134	1.430	0.625	1.068	1.438	1.385	1.243	3.405	5.295	2.378	0.449	1.569
2016	1.516	1.567	1.986	0.567	1.176	1.145	1.397	1.182	1.540	0.695	1.049	1.443	1.560	1.299	3.362	5.273	2.596	0.436	1.600

Table F1: 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. In addition, we attribute federal customs evenly to all consumption expenditure on goods and services.

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, $\phi_{utilities} = \frac{2}{3}$. For customs, we assume $\phi_{customs} = 80\%$.

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_{jst}^{pretax}, as the base. The federal tax rate can then be calculated as

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

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

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

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 (F1), as

$$T^{Ex}_{ijst} = \frac{t_{jst} + t_{jFt}}{1 + t_{jFt} + t_{jst}} \cdot c^{IMP}_{jt}\left(y_{is}\right). \tag{F2}$$

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:

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

G Property Taxes

G.1 Imputing Property Taxes Paid by Homeowners

As described in Section 2.8, 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.[70] 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 G1, 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.

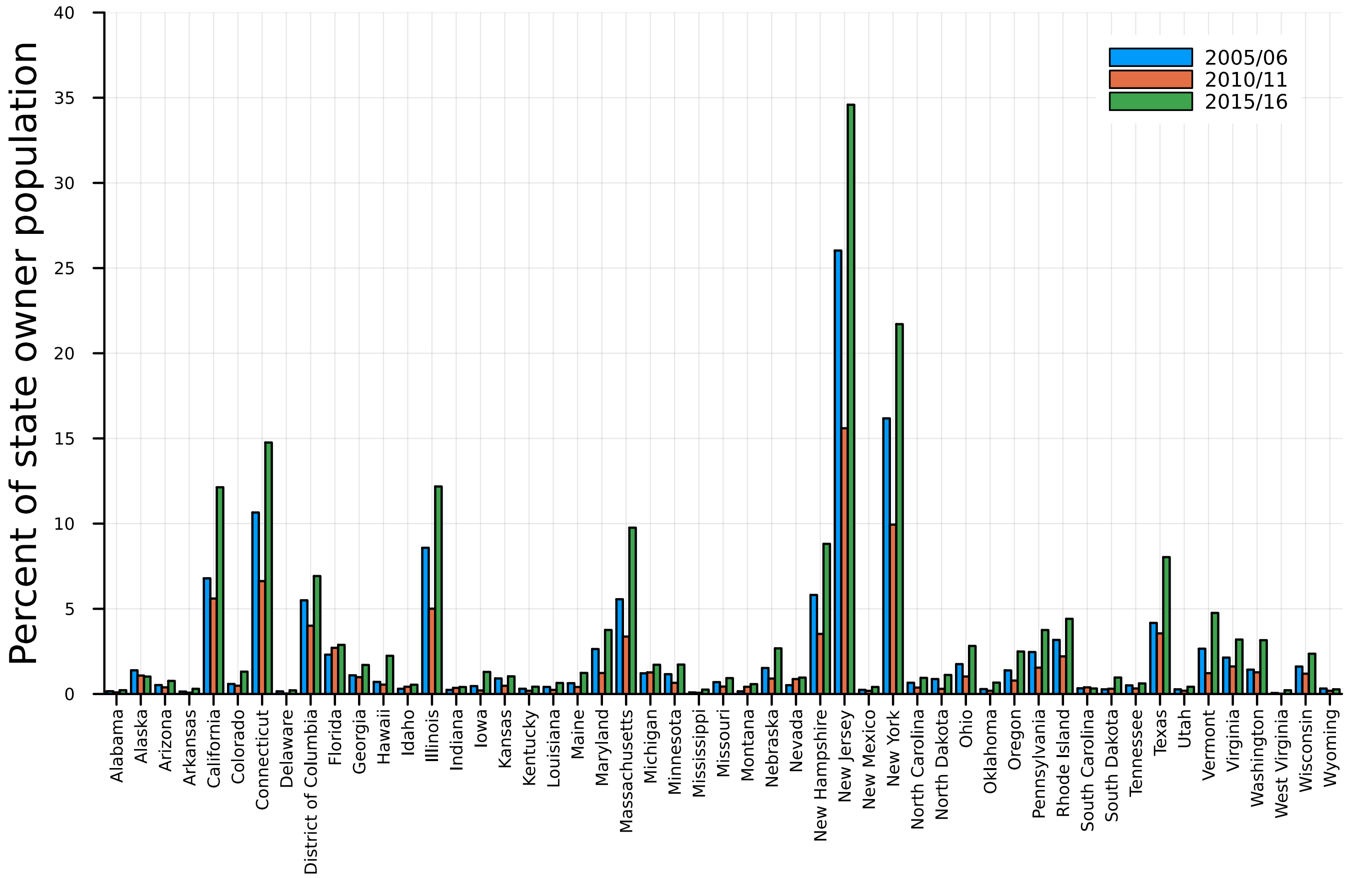

Figure G1: Share of ACS home owners with reported property taxes at the top-code ($10,000). Computed using the baseline selection conditions and ACS household weights. Refers to 2015/2016.

Furthermore, as the left panel of Figure G2 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.[71] To

[70] 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.

[71] As shown in Table D1 in Appendix D, we use IRS-SOI property tax data for about 60 percent of ASEC households in the highest income

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 G2 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.[72] Moreover, almost all top-coded households are in the highest income group, where their share is just below 8 percent.

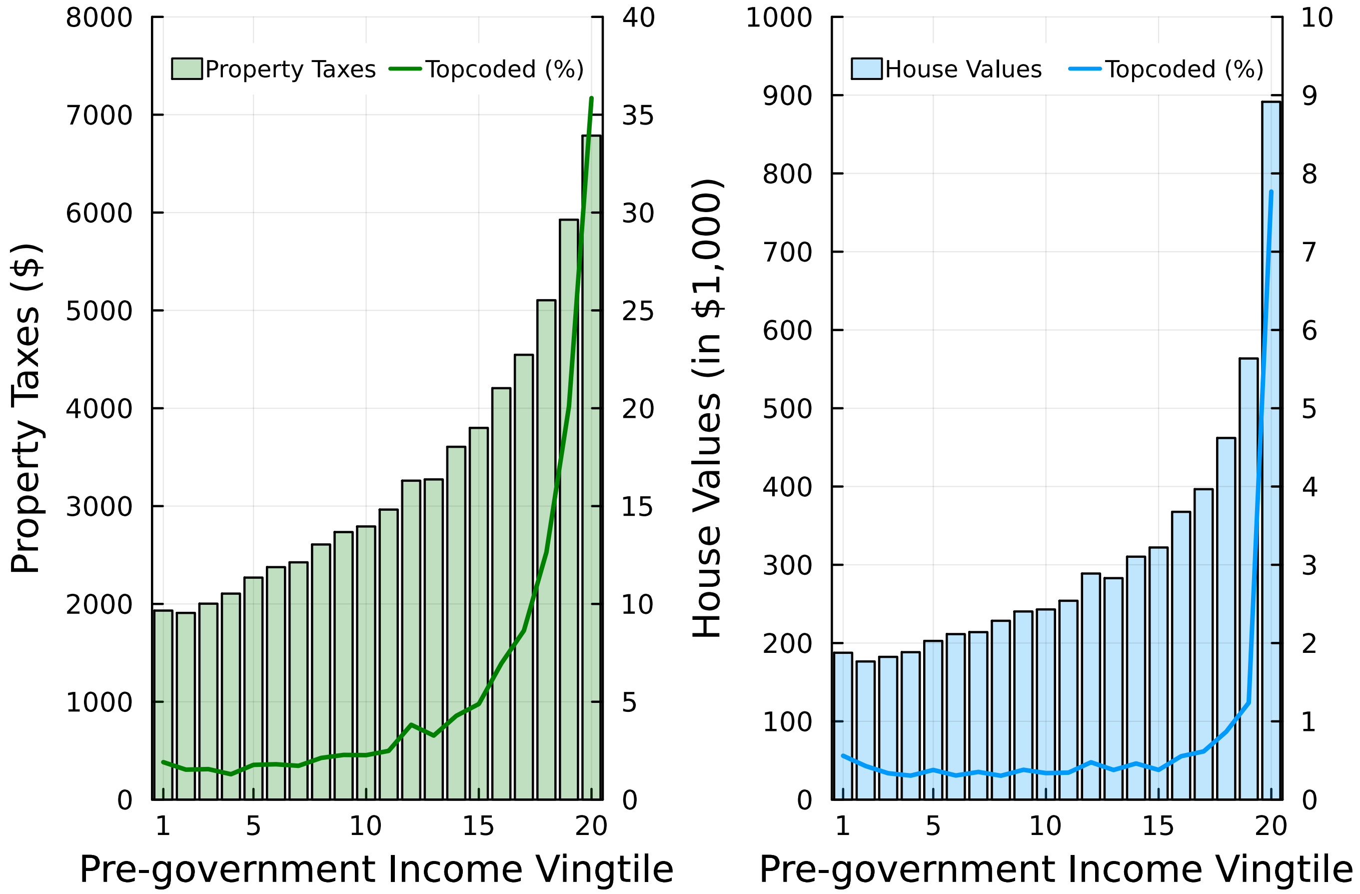

Figure G2: Left panel shows mean property taxes (left) and share at top-code (right) by income vingtile for the baseline sample. Right panel shows analogous means for house values. Source: ACS (2015/2016)

Specifically, we replace top-coded ACS property tax values as follows. For each year and state, we compute household level effective property tax rates for owners who report property taxes below the top-code by dividing their reported property taxes by their reported home values (we drop a small number of households who report higher property taxes than house values or for whom either is missing).[73] Next, for all households who are at the property tax top-code, we impute property taxes by multiplying their reported house values with the median measured property tax rate in their state, which we denote $t^p_{s,t}$.

Next, we match ASEC owners to ACS owners. First, we identify as many counties as possible in the ACS using PUMA-county equivalency files.[74] 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,

decile.

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

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

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

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.[75]

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

$$P_{i,c,t} = \text{Gross Rent}_{i,c,t} \times \beta_{c,t}, \tag{G1}$$

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:

$$T_{i,c,t} = P_{i,c,t} \times t^p_{s,t} \tag{G2}$$

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 $\gamma_{c,t}$:

$$\text{Renter Property Taxes}_{i,c,t} = \gamma_{c,t} \times T_{i,c,t}. \tag{G3}$$

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

[75] 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.

G.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 (G3). 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

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

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

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

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

Going back to the investment return equation, 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).[76]

Figure G3 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).

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

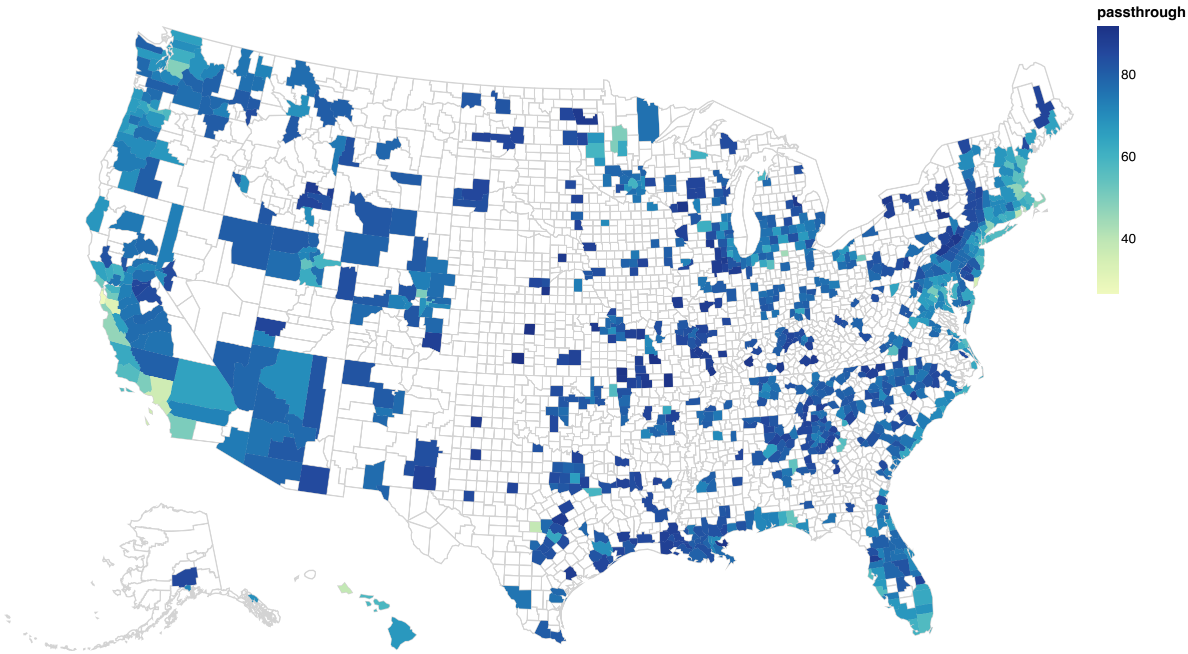

Figure G3: Property tax pass-through for renters by county, in percent. Computed as described in Appendix G.3 using 2012-2017 ACS multi-year data.

G.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 (G4) summarizes the main determinants of property taxes paid by household i on property j in year t in locality c:

$$T^P_{j,c,t,i} = \min\left\{ cb_{c,t} \times y_{c,t,i}\,,\left(\sum_{j=1}^{K} t^P_{t,c,k} \times \left(asr_{j,c,t} \times apr_{j,c,t} \times V_{j,c,t} - E_{j,c,t,i}\right)\right) - TC_{c,t,i} \right\} \tag{G4}$$

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.[77]

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

$$asr_{j,c,t} \times apr_{j,c,t} \times V_{j,c,t} - E_{j,c,t,i}. \tag{G5}$$

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.

[77] 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.

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:

$$t^P_{j,c,t} = \sum_{k=1}^{K} t^P_{c,t,k}. \tag{G6}$$

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.[78]

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.[79]

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

$$T^P_{j,c,t,i} = \min\left\{cb_{c,t} \times y_{c,t,i}, \text{Property Taxes After Credits}\right\}, \tag{G7}$$

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.

G.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 6 in Section 2.8 and Tables 5, D1

[78] 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.

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

and D2, 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).[80] Answering this question from an empirical perspective is challenging, because as illustrated by equation (G4), 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_i^P, house values V_i, incomes y_i and locations of residence (county or state). Hence, to investigate the drivers of property tax regressivity, we are restricted to a narrow set of variables. But we can decompose property taxes relative to income as the product of home values relative to income and effective property tax rates (i.e., property taxes relative to value):

$$\frac{T_i^P}{y_i} = \frac{V_i}{y_i} \times \frac{T_i^P}{V_i}. \tag{G8}$$

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 7 unequivocally answer this question in the affirmative: housing expenditures, either on more valuable houses or higher rents, are non-homothetic and only slowly increase in current income.

To illustrate this source of property tax regressivity more clearly, Figure G4 plots the same data as Figure 7 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.[81] 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

[80] 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.

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

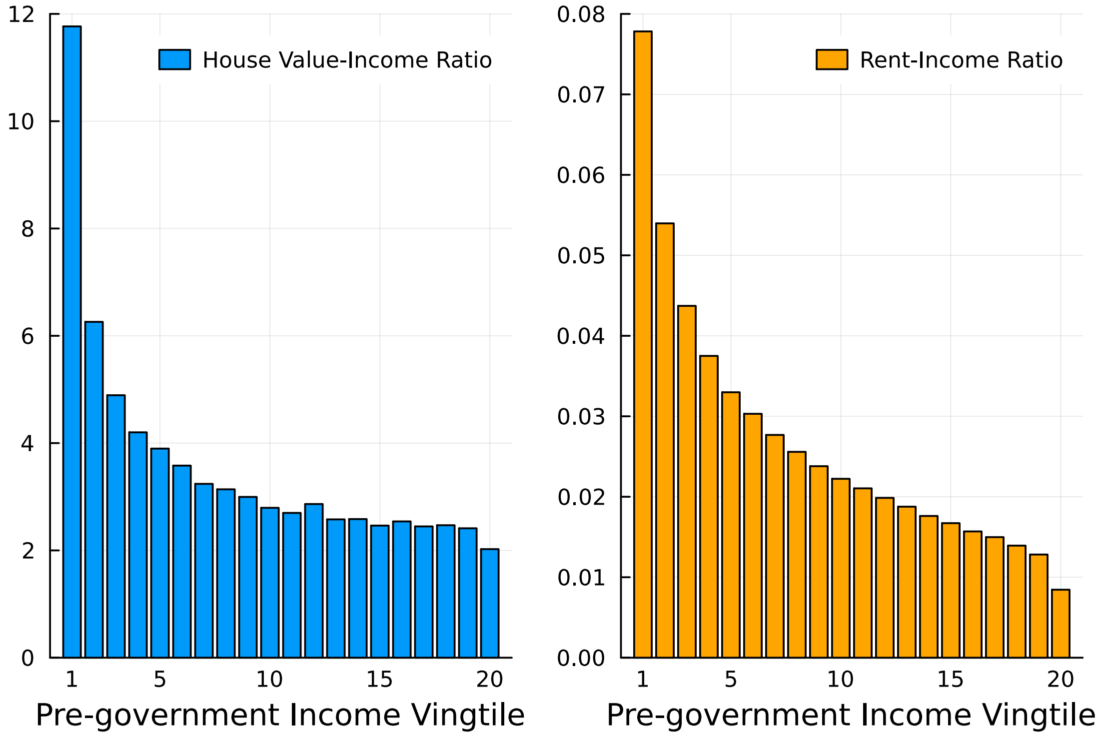

Figure G4: House value-income ratios (for owners; left) and gross rent-income ratios (for renters; right) by pre-government income. Each bar represents mean house values (rents) divided by mean pre-government income for each income vingtile, where households are ranked according to income. Source: ACS (2015/2016).

benefit from more favorable assessment ratios, as suggested by some of the literature cited above?

Figure G5 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 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.[82] 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 G6 separately plots the numerator and denominator (property taxes and house values) used to compute these rates. As previously illustrated by Figure G2, 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 G6 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

[82] Recall that our baseline sample excludes retirees.

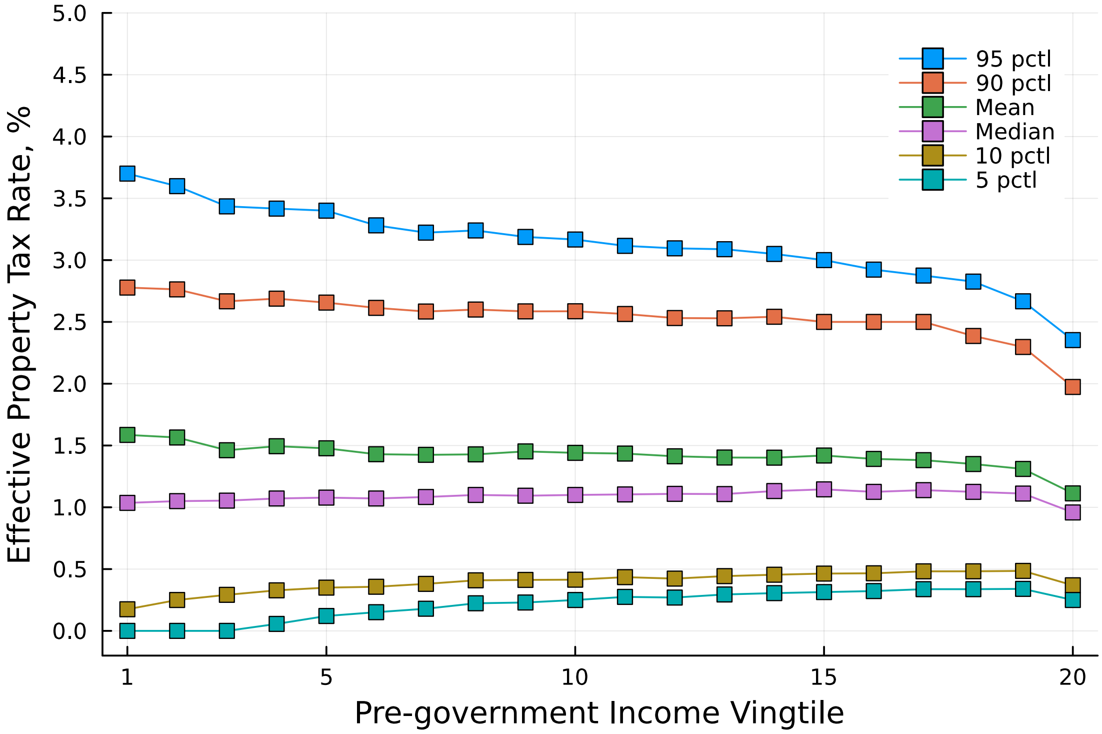

Figure G5: Mean effective property tax rates of owners in different income vingtiles (as well as mean and median), where households are ranked according to pre-government income. Source: ACS (2015/2016).

$6,000 to $6,900).

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

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

G.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

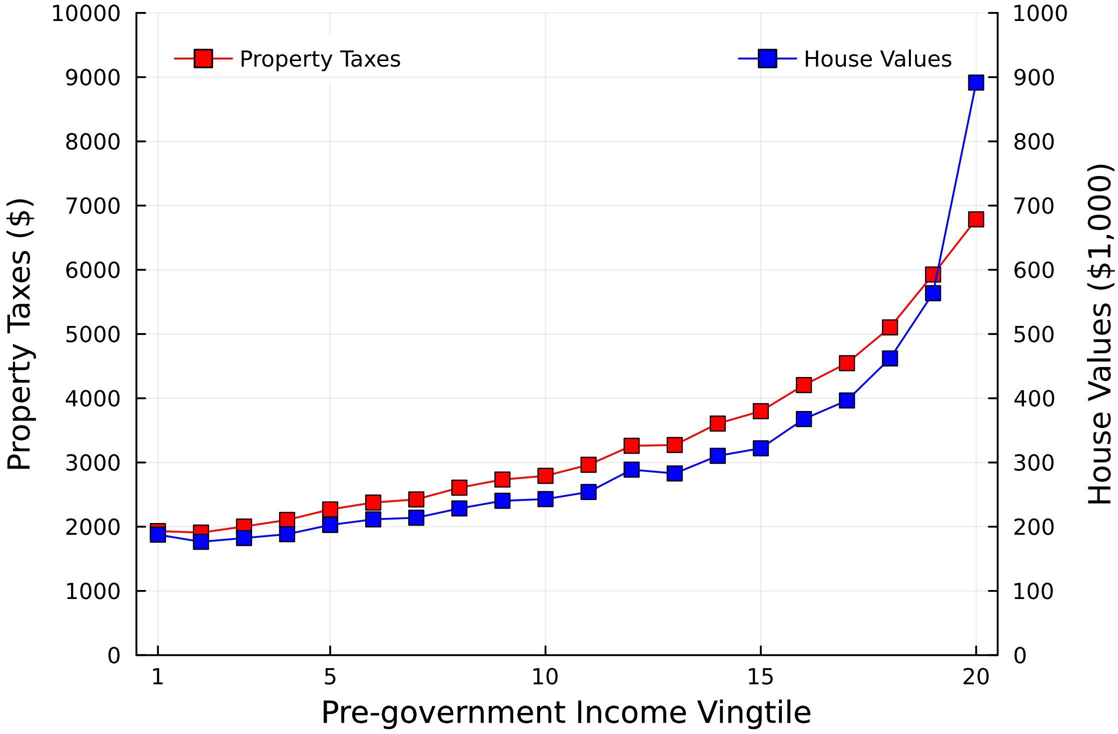

Figure G6: Mean property taxes (left) and house values (right, in $1,000) for ACS owner household in the baseline sample by income vingtile, where households are ranked according to pre-government income. Source: ACS (2015/2016).

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 G.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.[83] 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.[84] 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 G7. 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 G7 gives us confidence that our ACS-based property tax estimates accurately capture the extent of regressivity embedded in how property is taxed.

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

[84] 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.

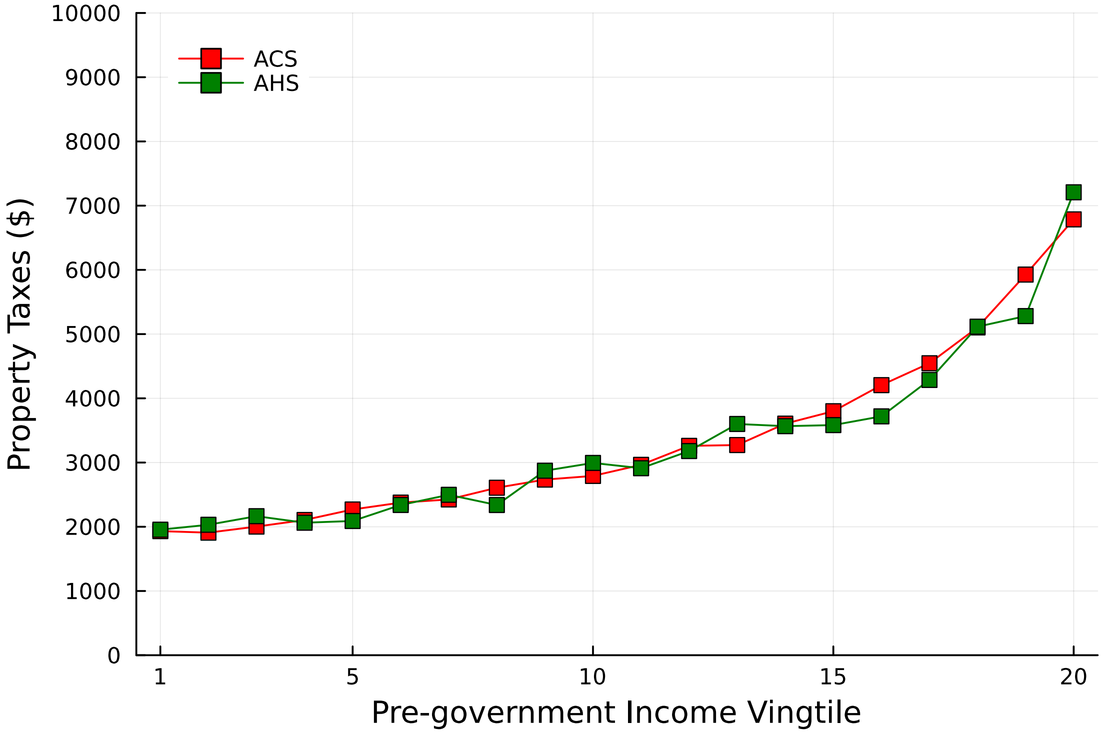

Figure G7: ACS and AHS mean property taxes by income vingtile using the baseline sample selection conditions. ACS (2015/2016), AHS (2015)

H 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 ASEC+ dataset with 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.[85]

Income Taxes Figure H1 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 E. 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.

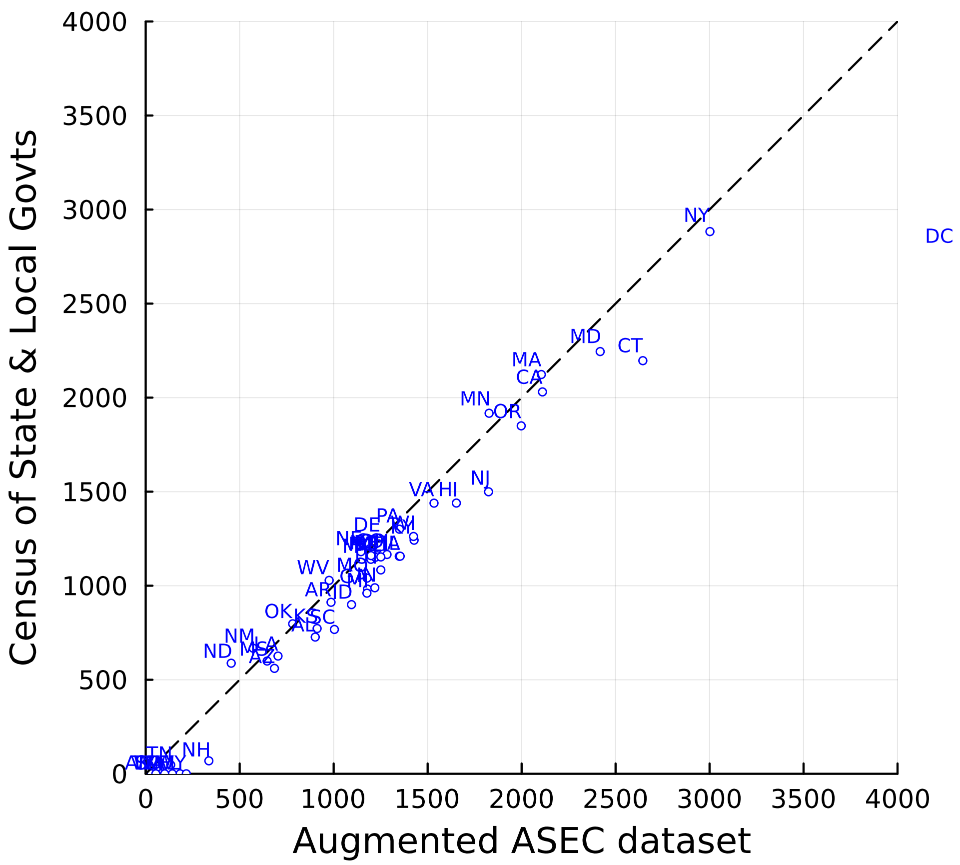

Figure H1: Per capita state and local income tax collections in current $, in the ASEC+ ("augmented") dataset (horizontal axis) and the CSLG (vertical axis) for 2015 and 2016. Computed using ASEC household weights.

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

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

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.

Property Taxes Figure H2 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 G.1.

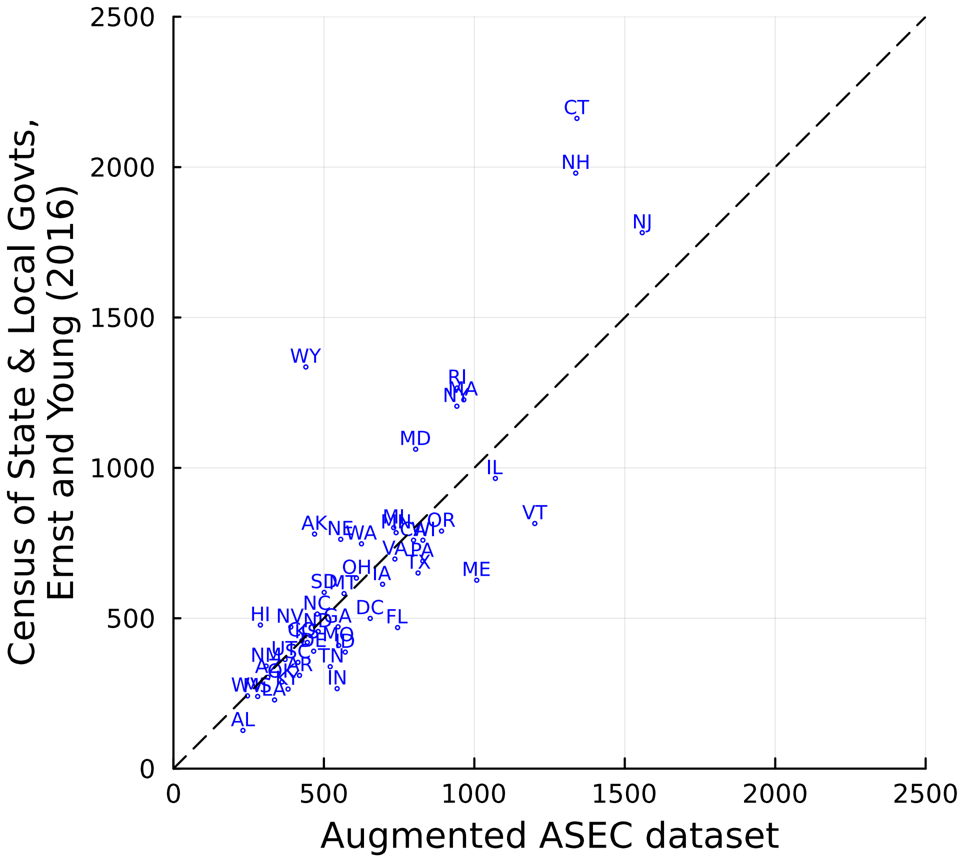

Figure H2: Per capita state and local household property tax collections in current $, in the ASEC+ dataset (horizontal axis) and the CSLG (vertical axis) for 2015 and 2016. Computed using ASEC household weights. Commercial property tax collections have been excluded using the data provided by Ernst & Young (2016).

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.

Consumption Taxes We impute sales and excise taxes for all ASEC households as described in Appendix F. Figure H3 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.

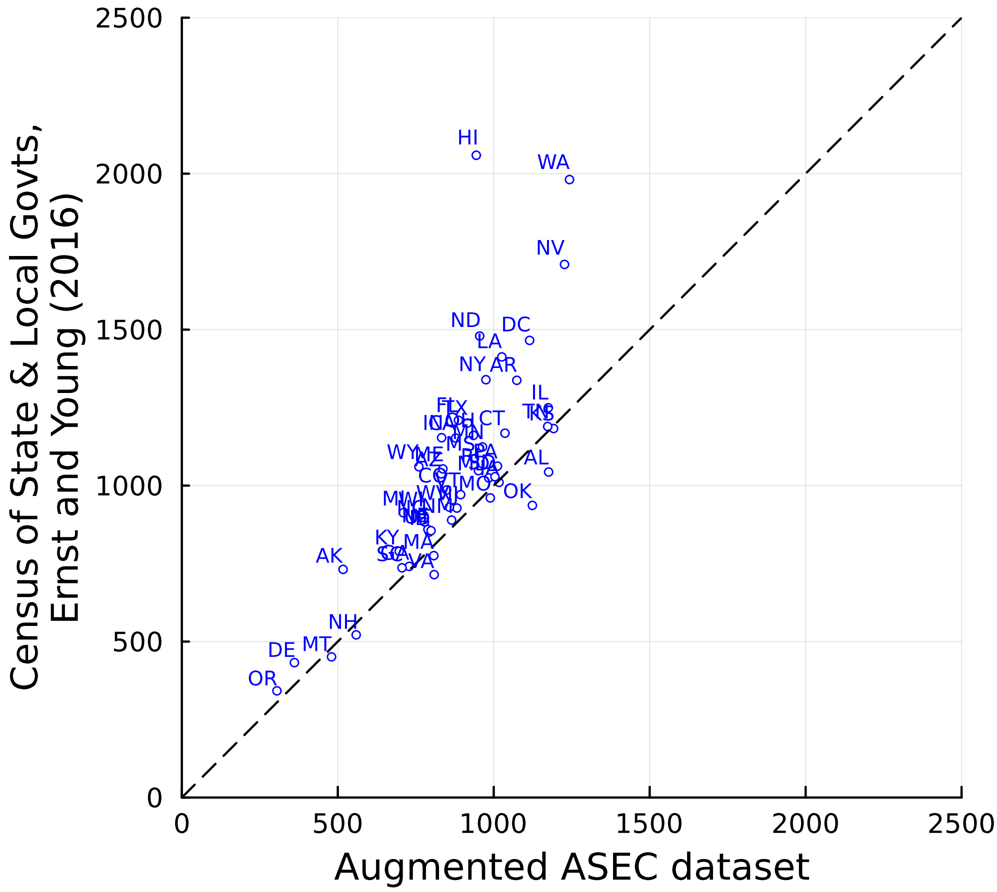

Figure H3: Per capita state and local consumption tax collections in current $, in the ASEC+ dataset (horizontal axis) and the CSLG (vertical axis) for 2015 and 2016. Computed using ASEC household weights. Business tax collections have been excluded using the data provided by Ernst & Young (2016) and as explained in Section F.

Overall, the administrative and imputed tax aggregates are strongly positively correlated, but the imputation model tends to assign lower taxes paid than the administrative benchmark, resulting in lower average tax rates. This is particularly true for some states—for example, Hawaii, Washington and Nevada. Recall that our model assumes all spending is done by state residents. But for Hawaii and Nevada, spending by tourists is an important additional source of revenue. Similarly, residents of states bordered by states with no sales tax (for instance, New Hampshire and Oregon) might be paying less consumption taxes than our model imputes. The discrepancies could also be due to Ernst & 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.

I 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.

I.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

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

I.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.[86] 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.[87]

I.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[88], 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).[89]

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.

[86] 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.
[87] The quantile q is always calculated at the national level.
[88] See here: https://obamawhitehouse.archives.gov/omb/budget/Historicals.
[89] Note that dividend income is self-reported in ASEC, while ordinary dividend income is a separate line item in the IRS-SOI tables.

J 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 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)[90] 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.[91]

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

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

Thus, the effective tax rate on local labor is

$$t^{m_L}_{s,t} = \frac{\alpha^{tr}_{s,t} R^m_{s,t}}{Y^L_{s,t}}. \tag{J1}$$

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.[92]

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

$$t^{m_C}_{s,t} = \frac{(1-\alpha^{tr}_{s,t}) R^m_{s,t}}{C^{ntr}_{s,t}}. \tag{J2}$$

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 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 G.2 and G.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.[93] Let $Y^B_{s,t}$ be total business income in state s and year t, estimated from BEA data.[94]

The effective property tax rate that falls on business owners is

$$t^{h_B}_{s,t} = \frac{\alpha^{land}_{s,t} \hat{R}^h_{s,t}}{Y^B_{s,t}}. \tag{J3}$$

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

personal-income-by-state.

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

[93]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.

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

tradable share falling on workers and the non-tradable share falling on consumers. Respectively,

$$t_{s,t}^{h_L} = \frac{\alpha_{s,t}^{tr}\left(1-\alpha_{s,t}^{land}\right)\hat{R}_{s,t}^{h}}{Y_{s,t}^{L}}, \tag{J4}$$

and

$$t_{s,t}^{h_C} = \frac{\left(1-\alpha_{s,t}^{tr}\right)\left(1-\alpha_{s,t}^{land}\right)\hat{R}_{s,t}^{h}}{C_{s,t}^{ntr}}. \tag{J5}$$

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

Figure J1 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).

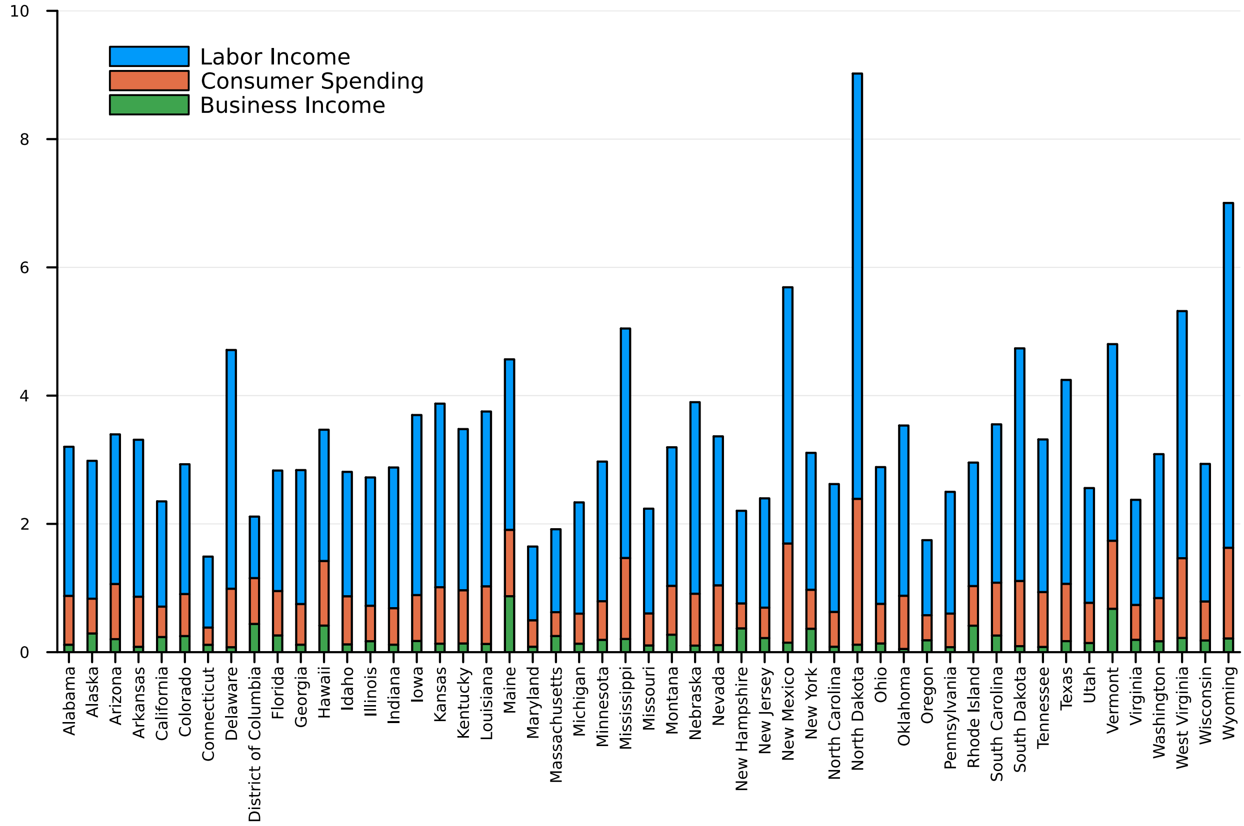

Figure J1: Effective business tax rates by state (2015/2016). Computed by dividing total state household gross income by total taxes paid using the entire augmented ASEC dataset and household weights.

K Estate Taxes

Our perspective on estate taxes is that they are paid by the decedent. Note that estate taxes do not appear in national income, so their is no income counterpart to estate taxes paid.

Information on federal estate tax paid is available from the IRS SOI Tax Stats - Estate tax filing year tables. We take data on net estate taxes paid from Table 2. We focus on tax filing years 2006 and 2007, 2011 and 2012, and 2016 and 2017 for our three two-year pairs (returns are typically filed in the year after the decedent's death). We target the average net taxes paid across each pair of years. In a handful of states in which very few returns were filed, the net amount paid is not reported. For those states we assume that the average net tax due, per return filed, was equal to the U.S. average.

We take data on net *state* estate taxes paid from the U.S. Census Bureau State Government Tax Tables. We take these taxes from the line "Death and Gift Taxes" (Tax Code T50). We use fiscal years 2005, 2011, and 2016.

We need to take a stand on how these taxes are distributed across households. For this we use the IRS Tax Stats - Linked estate tax - Form 1040 data tables. These tables, which are available only for Filing Year 2008, provide income from 1040 tax returns filed by decedents in the year prior to death. We use Tables 3 and 4 which provide information on federal net estate taxes paid by age group and income group for decedents who filed married 1040 returns in the prior year (Table 3) and non-married returns (Table 4). We combine both tables to compute the following distribution of total net estate taxes paid by Adjusted Gross Income bin.

AGI bracket	Share of federal estate taxes paid
Under $100,000	12.4%
$100,000 to $200,000	14.9%
$200,000 to $500,000	23.1%
$500,000 to $1,000,000	16.2%
More than $1,000,000	33.4%

For each state we allocate total federal estate taxes paid in a given year across households in accordance with this distribution. For example, we identify all households with WPA income below $100,000 in our ASEC+ sample in a given state, assume that each such household pays identical estate taxes, and set that amount so that, in total, this income group pays 14.9% of the total federal estate taxes paid in the state. For earlier years, the SOI income bins that we use to impute income to high income households in our ASEC+ sample are coarser than those in this table. For those years we merge the bins in the tax incidence table accordingly. We assume that the same incidence distribution for estate taxes by income applies to state estate taxes as for federal estate taxes, and that the distribution is identical to the one in the table above for all the years in our sample.

Note that our assumption on the distribution of estate taxes is counterfactual, in the sense that in reality a handful of decedents pay very large estate taxes. For example, in filing year 2017, only 5,185 returns had net taxes due, and the average amount due was $3.85 million. In contrast, we impose unconditional average expected taxes conditional on income. Note, however, that this distinction is immaterial for the question of how progressive estate taxes are: the vast majority of these taxes are paid by high income households.

L Affordable Care Act Provisions

The Affordable Care Act (ACA) of 2010 introduced three new provisions that affect our calculation of taxes and transfers: the Premium Tax Credit (PTC), which we treat as a tax credit, the individual Shared Responsibility Payment (SRP), which we treat as a tax, and the Cost Sharing Reduction (CSR), which we treat as a transfer. Since all three were effective starting in 2014, they only show up in taxes and transfers for years 2015-16. In those years, ASEC has enough variables available to identify whether an individual was covered by health insurance and, if so, which type (Medicare, Medicaid/CHIP, Military/VA, employer-sponsored, directly purchased on the market).

Premium Tax Credits (PTC). They are tax credits that eligible households receive when they purchase health insurance through the marketplace. It has the goal of making individual health insurance affordable for middle- and lower-income households by subsidizing premia. Eligible households are those with modified adjusted gross income (AGI) between 100% and 400% of the Federal Poverty Line (FPL) who purchased health insurance through an ACA marketplace.

The formula for the PTC for eligible households is

$$PTC = \max \{0, SLCSP - ECR \times AGI\}$$

where $SLCSP$ is the Second-Lowest-Cost Silver Plan. We set this value to $6,000 per year based on data from the KFF.[95] ECR is the household Expected Contribution Rate which follows a sliding scale that rises with income as a share of the FPL, which we closely approximate as

$$ECR = \begin{cases} 0.02 & \text{if } AGI < 1.33 \times FPL \\ 0.025 \times \left(\frac{AGI}{FPL}\right) & \text{otherwise} \end{cases}$$

Finally, we know from IRS data that total spending on PTC equals approximately $18.1B in 2015 and $22.2B in 2016, thus we rescale proportionately all individual amounts to match those totals.[96]

Individual Shared Responsibility Payments. They are a federal tax penalty for not having minimum essential health insurance coverage (or an exemption from it). From ASEC, we identify which member of the household is uninsured. First, we check whether individuals are exempt from the penalty. There are several exemption criteria, but there are only three we can accurately check (and as a result this procedure gives us an upper bound for the penalty):

1. The household resides in a state that had not yet expanded Medicaid by 2016: Alabama, Florida, Georgia, Idaho, Kansas, Louisiana, Maine, Mississippi, Missouri, Nebraska, North Carolina, Oklahoma, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, Wisconsin, Wyoming.
2. Household modified AGI is below the filing threshold: $10,300 for singles, $20,600 for married couples and $13,250 for heads of households younger than 65. And $11,900 for singles, $23,200 for married couples and

[95] See https://www.kff.org/affordable-care-act/state-indicator/average-marketplace-premiums-by-metal-tier/.
[96] See https://www.irs.gov/pub/irs-soi/16inintaxreturns.pdf.

$14,800 for heads of households 65+.

3. Health insurance coverage for the household is deemed unaffordable, i.e. the Net of the PTC price of the Lowest-Cost Bronze Plan (NLCBP) is more than 8% of household income. According to the KFF, the gross cost of such plan would be around $2,500 per year, thus

$$NLCBP = \$2,500 - PTC$$

where PTC is calculated above.[97] If $NLCBP$ is above 8% of household AGI, the household is exempt.

If the household is not exempt, the SRP is computed as follows. Let FT be the filing income threshold.

For year 2015:

$$\begin{aligned} Percent &= 0.02 \times (AGI - FT) \\ Flat &= \max \{\$975,\ \$325 \times \text{uninsured adult} + \$162.5 \times \text{uninsured child}\} \\ SRP &= \min \{\max \{Percent, Flat\}, \$2,484 \times \text{\# of uninsured household members}\} \end{aligned}$$

For year 2016:

$$\begin{aligned} Percent &= 0.025 \times (AGI - FT) \\ Flat &= \max \{\$2,085, \$695 \times \text{\# of adults} + \$347.5 \times \text{\# of children}\} \\ SRP &= \min \{\max \{Percent, Flat\},\ \$2,676 \times \text{\# of uninsured household members}\} \end{aligned}$$

According to the IRS, the total amount of penalties paid was $3.1B in 2015 and $3.6B in 2016.[98] We rescale proportionately individual amounts to match those totals.

Cost Sharing Reductions (CSR). They are federal subsidies that lower out-of-pocket health care costs such as deductibles, copays, coinsurance, and the annual out-of-pocket maximum.

From ASEC, we identify which member of the household has health insurance coverage purchased directly from the marketplace. Eligible households are those with AGI between 100–250% of the Federal Poverty Level (FPL). In principle, the subsidy applies only to those who purchase a Silver Plan, but we don't have this information in the data, and thus we opt for a simple imputation. Based on the Office of Management and Budget Historical Table 11.3 *Outlays for Payments for Individuals by Category and Major Program: 1940-2024*, the national amount of spending on Refundable Premium Tax Credit and Cost Sharing Reductions was $27.2B in 2015 and $ 30.8B in 2016.[99] To obtain the total amount spent on CSR, we subtract the total spending on PTC (see above) from these amounts, and obtain that aggregate spending for CSR was $9.1B in 2015 and $8.6B in 2016. We divide this amount equally across all eligible households.

[97]See https://www.kff.org/affordable-care-act/state-indicator/average-marketplace-premiums-by-metal-tier/
[98]See https://www.irs.gov/pub/irs-soi/16inintaxreturns.pdf.
[99]See https://www.whitehouse.gov/omb/information-resources/budget/historical-tables/.

M Transfers

We now give additional details on seven transfer programs: the Supplemental Nutrition Assistance Program (SNAP, "Food Stamps"), Temporary Assistance for Needy Families (TANF), Housing Assistance, Pell Grants, Alaska Permanent Fund Dividends (APFD), Medicaid, and Medicare.

M.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."[100]

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.[101] 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.

M.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).[102] 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.[103] 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

[100] 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.

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

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

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

keep receiving the federal block grant, they must only continue to spend a fraction of their historical welfare spending.[104] As a result, the TANF program has two distinct features. First, even conditional on receiving the same per-capita amount of federal TANF funding, the actual use of funds varies drastically across states because each state sets its own rules on eligibility, generosity and duration. Schott, Pavetti, and Floyd (2015) and Hahn, Aron, Lou, Pratt, and Okoli (2017) document this feature of TANF in detail. Second, there is 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."

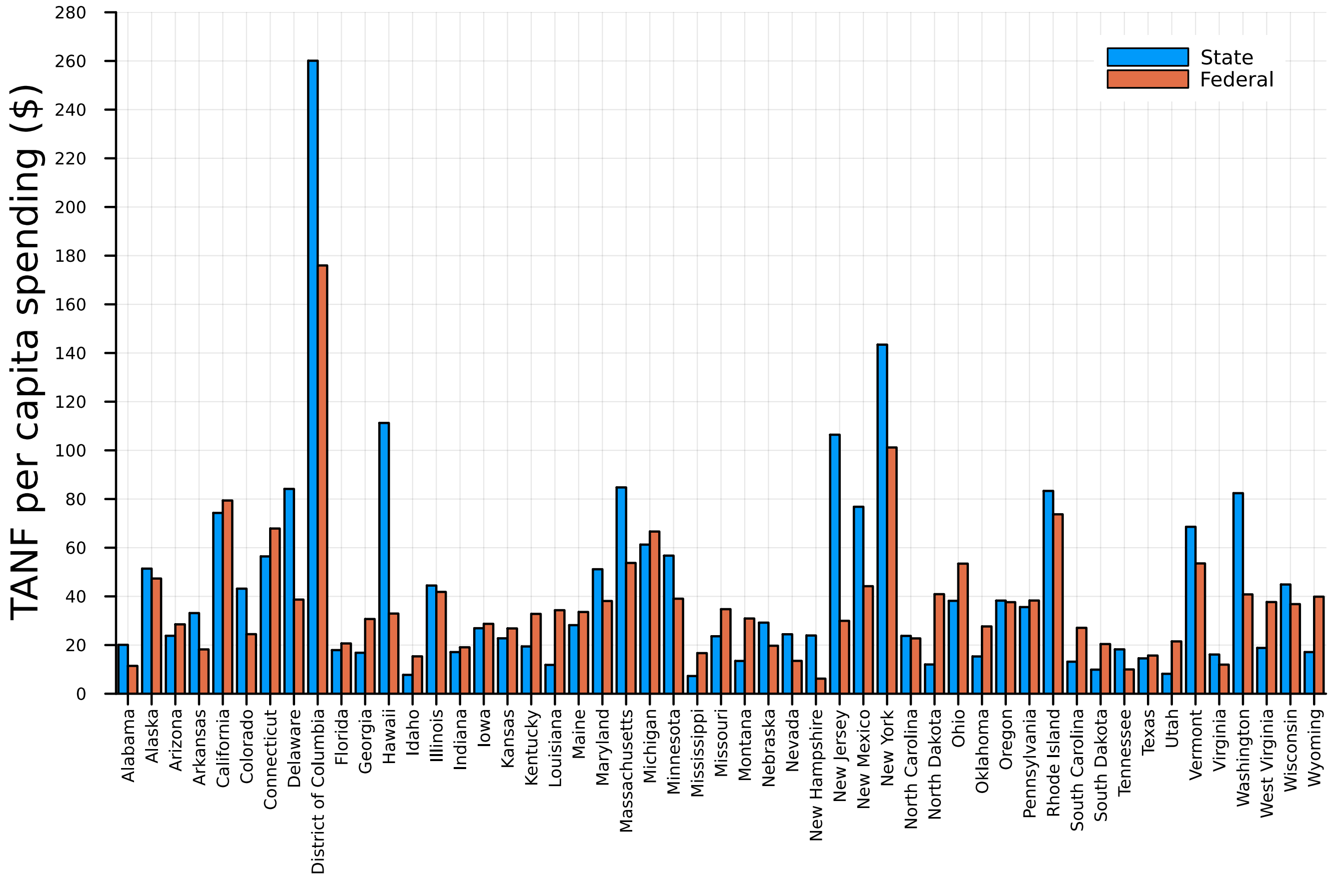

Figure M1: Federal and state per capita TANF spending in 2016. Computed from TANF financial data provided by the Office of Family Assistance (OFA).

For 2016, Figure M1 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.[105] To split the reported numbers into federal and state components, we use program data from the Office of Family Assistance (OFA).[106]

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

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

[106] 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

M.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).[107] To measure the household transfers provided by federal housing assistance support, we use the respective variable imputed into the ASEC dataset by the CBO.[108]

M.4 Pell Grants

ASEC contains two variables useful to assess whether someone was a recipient of a Pell grant and the grant size. The variable INCEDUC indicates how much pre-tax income (if any) the respondent received for (post high-school) educational assistance from all possible sources outside the household during the previous calendar year. The variable SRCEDUC indicates all the specific sources of such assistance, i.e. Pell Grants or other aid from government sources, institutional scholarships and grants, and financial assistance from employers or friends.

Some individuals only report Pell grants as a source of assistance. For these, the variable INCEDUC allows to infer the size of the grant. However, some Pell grant receivers list multiple sources, and thus the income they received as educational assistance presumably exceeds the size of their grant. In order to capture the transfers more accurately, we therefore rescale proportionately the total amount received in educational assistance by each Pell grant recipient so that the ASEC sample total equals the official national total obtained from the Department of Education at https://studentaid.gov/data-center/student/title-iv.

M.5 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.[109] 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."[110] 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:

national mean of 42 percent (58 percent).

[107] 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.

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

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

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

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.

M.6 Medicaid and CHIP

Medicaid and the Children's Health Insurance Program (CHIP) provide medical assistance payments to certain individuals. According to Medicaid and the CHIP Payment and Access Commisson (2018b), Medicaid and CHIP expenditures in 2016 totalled \$583bn (equivalent to 3.1 percent of GDP) and represented about 17.4 percent of total national health expenditures.[111] 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.[112]

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.[113] 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

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

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

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

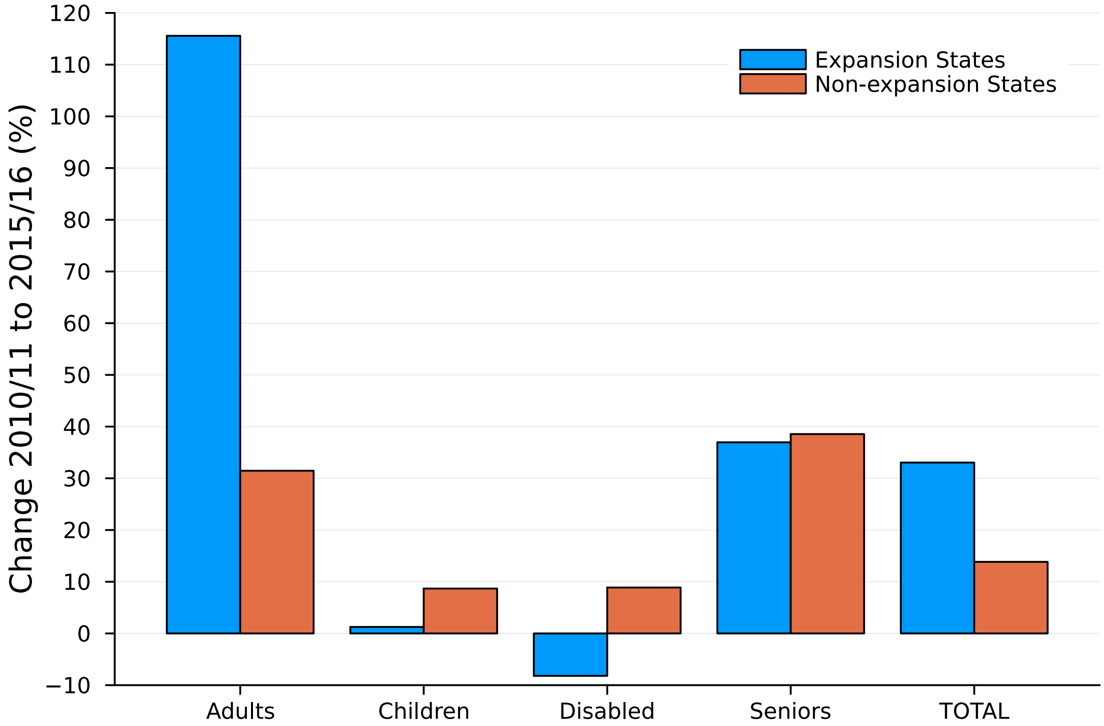

Figure M2: Change in Medicaid Enrollment by State between 2010/11 and 2015/16. Changes are computed using data provided by the Centers for Medicare & Medicaid Services (CMS), the Kaiser Family Foundation, and the Medicaid and CHIP Payment and Access Commission (MACPAC).

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 M2.

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.[114] 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).

To summarize the effect of Medicaid and CHIP’s mandatory and optional parameters, Figure M3 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.

[114] 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.

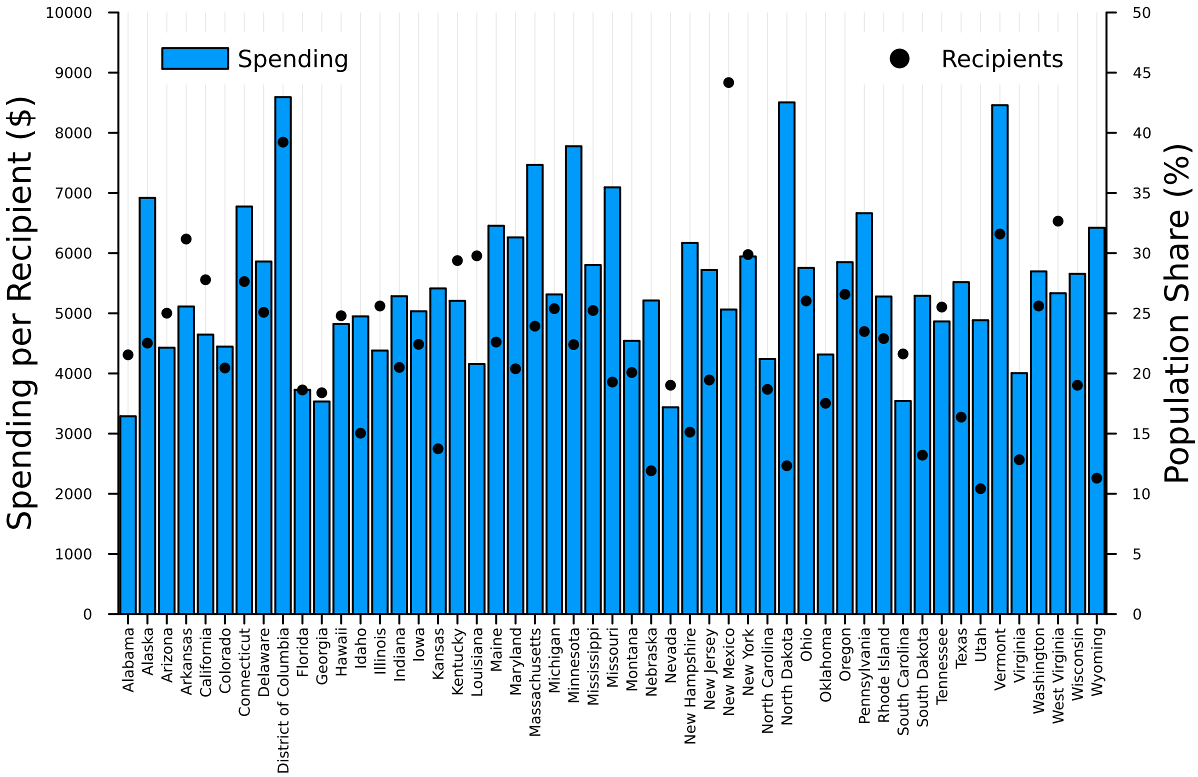

Figure M3: Medicaid spending per recipient (left axis) and Medicaid recipients as share of state population (right axis), 2016. Recipients include part-year recipients. Source: Centers for Medicare & Medicaid Services (CMS), Kaiser Family Foundation, Medicaid and CHIP Payment and Access Commission (MACPAC).

Measuring enrollment and transfer benefits in ASEC The ASEC survey asks respondents to report Medicaid or CHIP coverage. However, as documented by Habib (2018), coverage tends to be under-reported by almost 50 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 heterogeneity within enrollment groups to capture differences in within-year coverage periods.[115]

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

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

the CBO's algorithm by (i) targeting state-level enrollment numbers, and (ii) using state average spending for each enrollment group.[116]

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 for CHIP was 82 percent.[117] 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:

$$FMAP_{s,t} = \min\left\{ \max\left\{0.83, 1 - \frac{(y_{s,t})^2}{(y_{US,t})^2} \times 0.45\right\}, 0.5\right\}, \tag{M1}$$

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 M4 shows FMAPs for every state in our sample years.[118]

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).[119]

M.7 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

[116] 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.

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

[118] 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.

[119] 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.

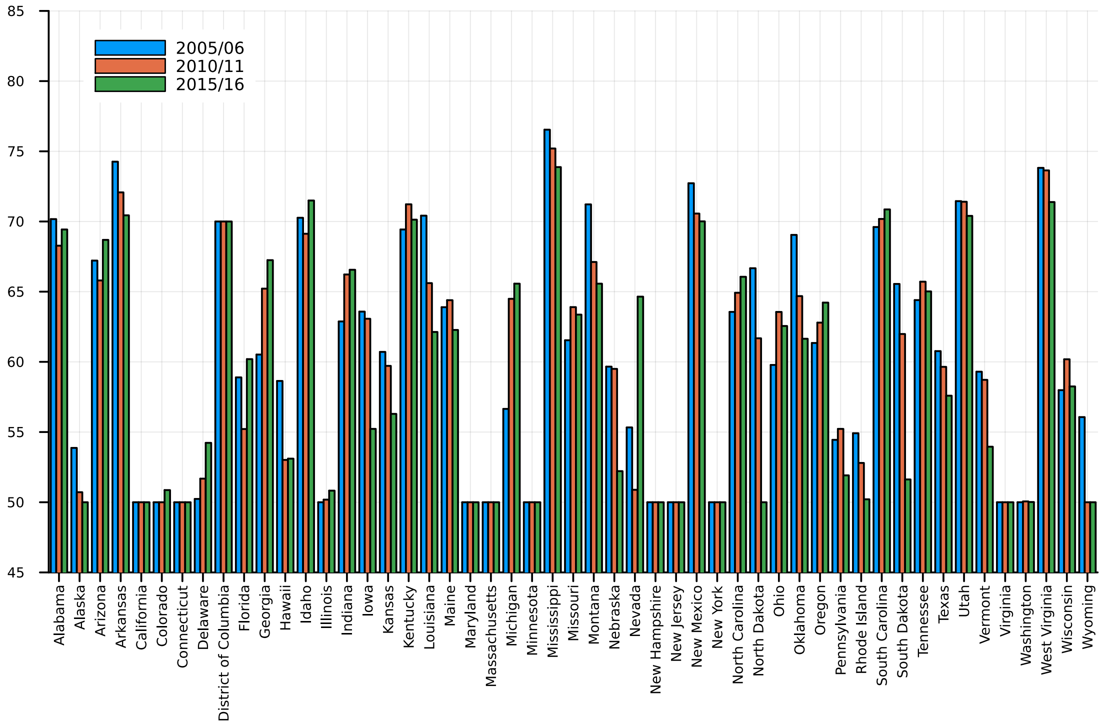

Figure M4: Federal Medicaid Assistance Percentages (FMAPs), averages of adjacent years. Source: Federal Register.

is substantial because of regional differences in cost and utilization.[120]

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.[121] 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).[122]

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 M5.

Finally, to convert the public spending amounts into household cash values, we use an estimate from Finkelstein and McKnight (2008), who found that eligibility for Medicare reduced the 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.

[120] 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."

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

[122] 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.

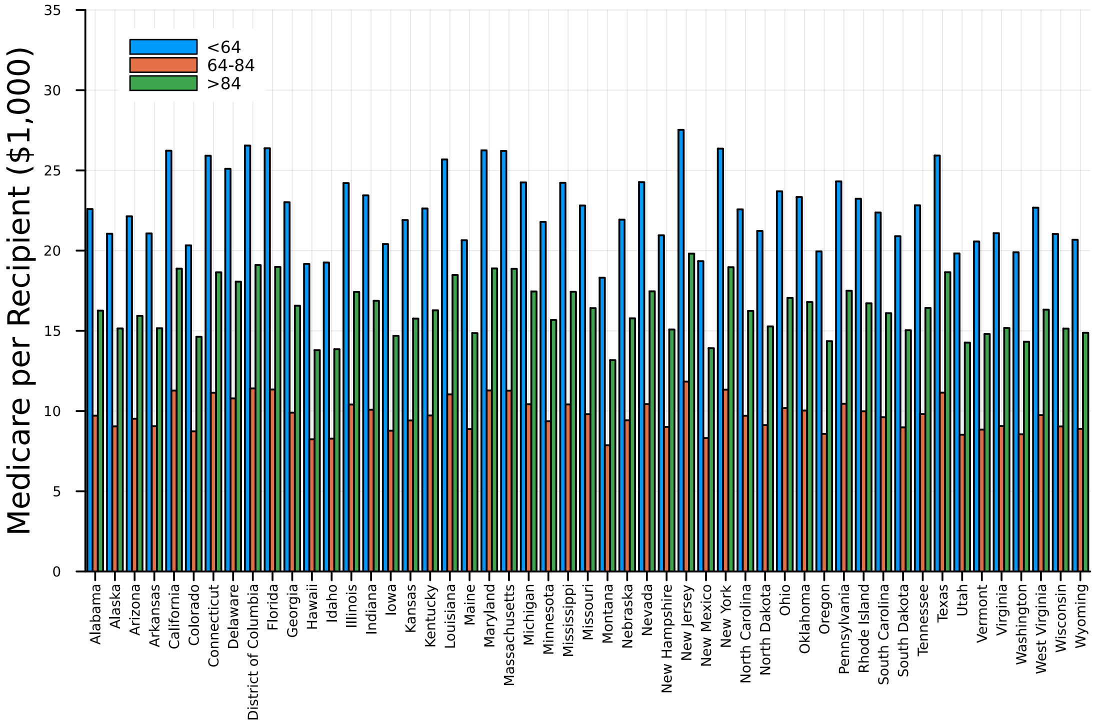

Figure M5: Average Medicare per Enrollee Spending in 2016 for three different age groups. Source: Centers for Medicare & Medicaid Services and authors' computations.

N 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 $j = 1, ..., 10$:

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

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:

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

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

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

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

Figure N1 illustrates the effect of this reweighting procedure on state income distributions. Using the new weights aligns them closely to the national distribution.

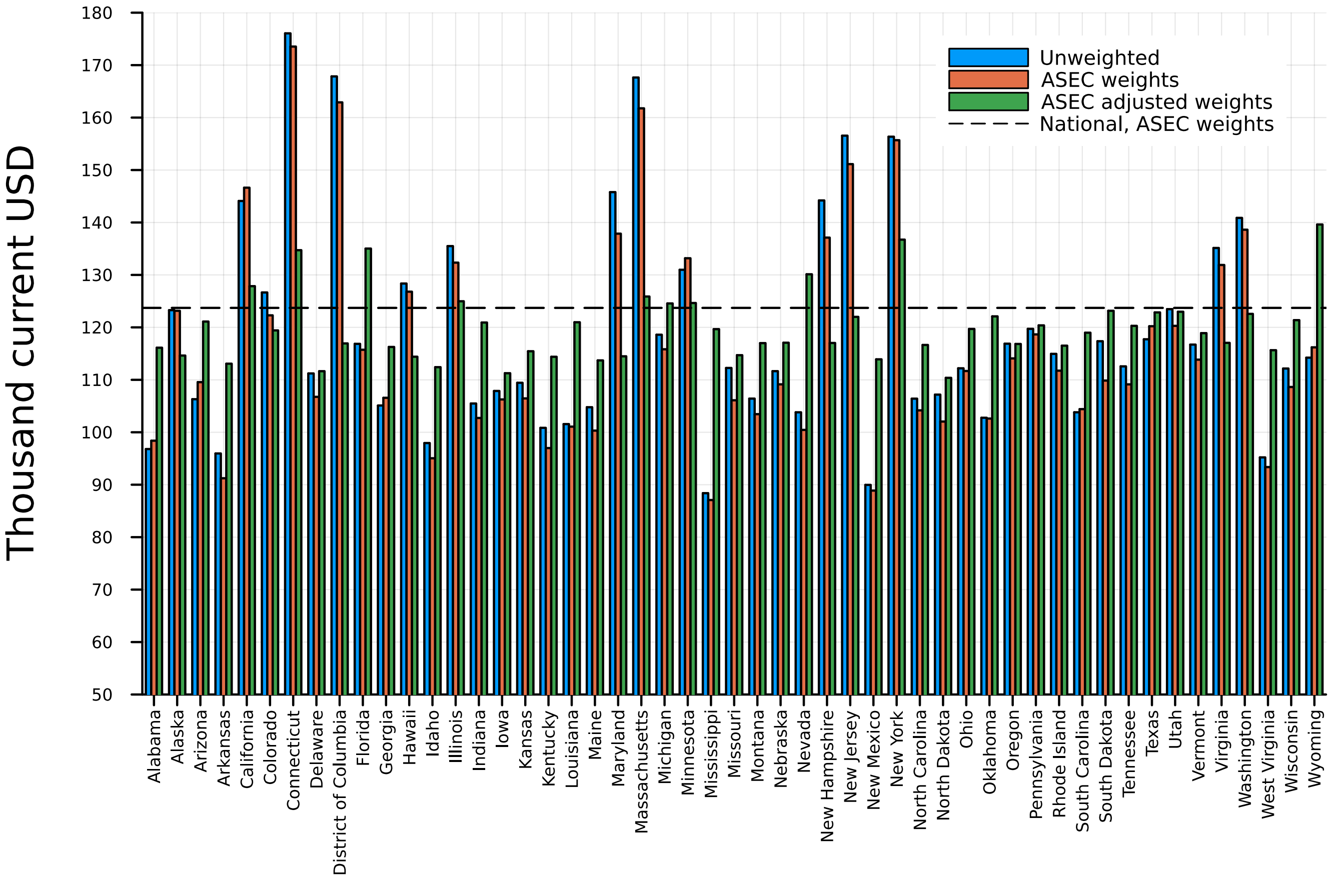

Figure N1: Means of ASEC sample household income distributions using different (no) weights (2015/2016).

O More Results on Baseline State Progressivity

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

O.1 Differences in the Cross-Section

Figure O1 plots the contributions to overall state progressivity shown in Figure 22 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.

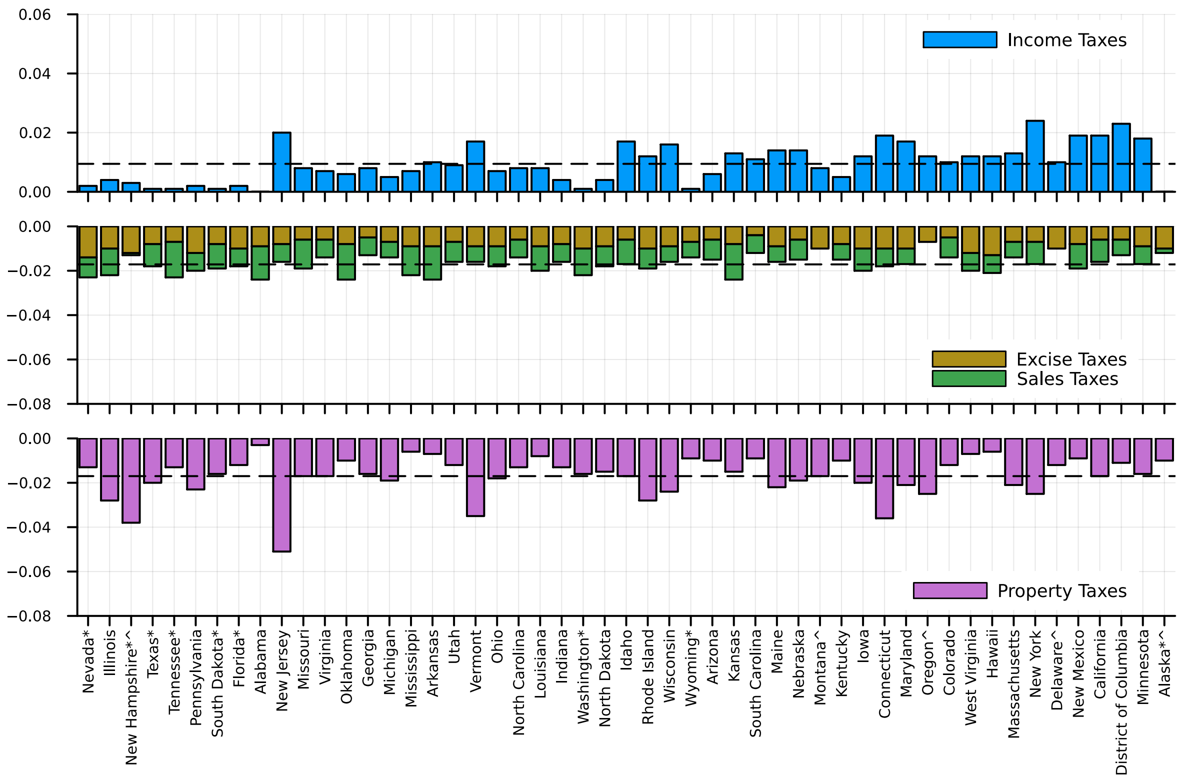

Figure O1: State level contributions to state progressivity, τ_s, (or regressivity if negative) from income, sales and excise and property taxes. Horizontal dashed lines are unweighted state averages. Estimates are for 2015/2016. See notes to Figure 22.

O.2 Differences over Time

Table O1 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) only corporate income taxes, (vi) only business taxes, (vii) all state transfers (but no taxes), (viii) only unemployment insurance benefits, (ix) only the state component of Medicaid, (x) 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.

	2005/06		2010/11		2015/16		Correlations	
	mean	stdev	mean	stdev	mean	stdev	2005/06–2010/11	2010/11–2015/16
Baseline	0.001	0.012	0.005	0.013	0.001	0.015	0.86	0.81
Taxes	-0.015	0.006	-0.019	0.008	-0.016	0.007	0.83	0.87
Income	0.007	0.005	0.008	0.005	0.009	0.006	0.89	0.93
Property	-0.008	0.005	-0.012	0.006	-0.011	0.006	0.92	0.95
Sales and Excise	-0.013	0.002	-0.014	0.003	-0.013	0.003	0.88	0.89
Corporate Income	0.002	0.001	0.002	0.001	0.002	0.001	0.81	0.55
Business	-0.004	0.003	-0.004	0.005	-0.004	0.003	0.78	0.71
Transfers	0.016	0.008	0.022	0.008	0.017	0.010	0.78	0.72
Unemployment Insurance	0.004	0.002	0.012	0.005	0.003	0.002	0.55	0.29
Medicaid	0.009	0.004	0.008	0.004	0.012	0.005	0.86	0.80
Other	0.003	0.004	0.002	0.004	0.002	0.006	0.91	0.92

Table O1: 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.

Figure O2 provides more details on time variation at the state level. It plots estimated progressivity in 2005/2006 on the horizontal axis against estimated progressivity in 2010/2011 (green) and in 2015/2016 (blue) on the vertical axis and shows their rank correlation coefficient. All dots (except for Alaska) are close to the 45 degree line, and the rank correlation is high, indicating our estimates capture persistent policy differences between state governments.

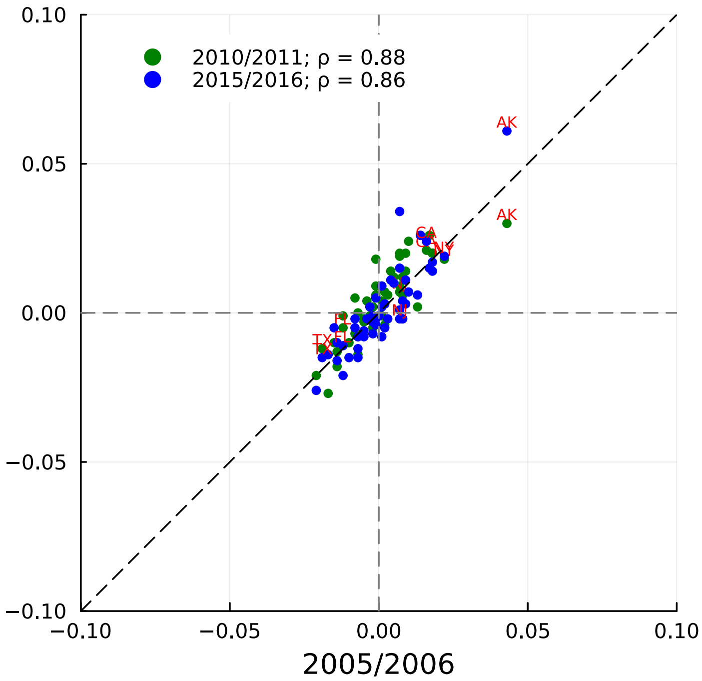

Figure O2: Time Variation in State Progressivity, τ_s. Estimate uses all state taxes and transfers (see Section 4.3); ρ is the Spearman's rank correlation coefficient for 2005/2006-2010/2011 and 2005/2006-2015/2016.

P Public Spending as a Transfer

In this extension, we explain how we incorporate public spending by all levels of government—local, state, and federal. We also analyze the impact of treating Medicare and Medicaid at full cost instead than at their estimated private value.

P.1 State and Local Spending

We obtain data on state and local spending from the State and Local Government Finances datasets of the Census Bureau for years 2005/2006, 2010/2011, and 2015/2016. We sum net spending (i.e. spending net of charges) by states and by local governments together. We divide state and local (prefix S) spending into four main categories: education (SEDU), health (SHEALTH), other publicly-provided private goods (SOTH), and pure public goods (SPURE). The residual (category SRES) is attributed proportionately to these four components. We organize spending this way because we use different imputation strategies for each of these four groups. Spending on education (SEDU) is imputed proportionately to the number of household members below age 18; spending on health (SHEALTH) and on other publicly-provided private goods (SOTH) are imputed lump-sum to households; spending on pure public goods (SPURE), instead, is imputed proportionately to household consumption expenditures. We explain the logic for this imputation strategy in the main text. Note that when imputing the per household, per student, and per consumption expenditure values we use the sum of state households, students, and consumption expenditures to scale administrative targets. Thus we are assuming that those benefits only accrue to state residents and have no spillovers across state borders.

To help the reader reconstructing our calculations, in our description below we also reference the line number corresponding to the 2016 Census Bureau Table on State and Local Government Finances.

Education (SEDU). We include all spending on education (line 69) which includes spending on higher education, elementary and secondary education, and other education. From these, we subtract education-related revenues (line 24) which include charges for institutions of higher education and school lunch sales.

Health (SHEALTH). We include only a subset of spending on social services and income maintenance. Namely, we include spending on hospitals (line 81) net of hospital charges (27), health (83), and veterans' medical care services (85). Note that these expenditures only include non-means-tested direct health services, and thus we don't need to net out state Medicaid which is already included in our measure of state transfers.

Other Publicly-Provided Private Goods (SOTH). We include spending on parks and recreation (line 99) net of charges (33), housing and community development (101) net of charges (34), utilities (line 113), i.e. water supply, electric power, gas supply, and public transit net of all revenue from utilities (43), plus a component called miscellaneous commercial activities (line 111) which refers to the provision and operation of commercial facilities not classified under particular functions.

Pure public goods (SPURE). This component includes spending on public transportation infrastructure net of its revenue, public safety, natural resources (i.e. conservation, promotion, and development of natural resources, such as soil, water, forests, minerals, and wildlife) net of related charges, some essential environmental services (sewerage and waste management) and governmental administration.

In particular it is constructed by summing spending on highways (line 86) net of charges (28), airports (88) net of charges (29), parking facilities (89) net of charges (30), sea and inland port facilities (90) net of charges (31); police protection (line 92), fire protection (93), correction (94), protective inspection and regulation (96); natural resources (line 97) net of charges (32); sewerage (102) net of charges (35), solid waste management (104) net of charges (36); financial administration (line 106), judicial and legal administration (107), general public buildings maintenance (108), other governmental administration, e.g. planning and zoning activities (109), and employment security administration, i.e. administration of unemployment compensation, public employment offices, and related services (line 84).

Residual spending (SRES). This residual component includes other and unallocable general expenditures, defined as general expenditure for purposes and activities not falling within any standard functional category and unallocated amounts relating to two or more functions (line 112) net of other charges (37) and net of other general revenue (42).

Finally, we note that our measure of net spending excludes (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 reflects revenues from interests on assets and sales of properties, (v) interest on general debt, because it is a form of spending that does not generate any value to households; and (vi) all spending on public welfare because all these payments are already included in our measures of transfers.

P.2 Federal Spending

We obtain data on federal spending mainly from NIPA Table 3.16, Government Current Expenditures by Function for 2005/2006, 2010/2011, and 2015/2016. Similarly to our analysis at the state and local level, we create separate groups for Federal (F prefix) spending which we impute to households as described above with one difference: we separate medical care spending for veterans from the rest of health spending because it is a sizable item, and because we can easily impute it to our ASEC households based on a survey variable which identifies veteran status among household members.

Education (FEDU). It includes spending on education (line 70) comprising of expenditures on elementary, secondary, higher and other education.

Health (FHEALTH). Federal spending on health (line 68) in NIPA includes production of health services which are paid for by households through Medicare and Medicaid, as well as through premium tax credits and cost sharing reduction subsidies. Unfortunately from NIPA it is impossible to tease out these components. Thus, to avoid double counting we resort to a different source, the Historical Tables of the Office of Management and Budget.[123] In particular, *Table 11.3 Outlays for Payments for Individuals by Category and Major Program: 1940-2024* contains all the different federal government payments to individuals for the purchase of medical care. The total in this table for year 2016, for example, is $1,197 billion versus $1,229 in the NIPA Table 3.16, thus the two amounts basically coincide. Based on these tables, we include in federal spending for health care the total amount (line 31) net of all the components we have already included in transfers, namely Medicare (lines 18 and 19) and CHIPS and Medicaid (lines 20 and 21), Refundable Premium Tax

[123] See https://www.whitehouse.gov/omb/information-resources/budget/historical-tables/.

Credit and Cost Sharing Reductions (line 28), and net of health care for veterans (line 23) which is treated as a separate spending group. The residual amount of this category for 2016 is only around $40 billion.

Health Care for Veterans (FVET). This component includes Hospital and medical care for veterans (line 23).

Other Publicly-Provided Private Goods (FOTH). This component includes housing and community services (line 67) and recreation and culture (69).

Pure public goods (FPURE). This component includes general public service spending for executive, legislative, tax collection and financial management (lines 44-45), national defense (48), public order and safety, i.e. police and fire protection, law courts and prisons (49), economic affairs, e.g. transportation, space, and other economic affairs such as energy, natural resources and postal service (54).

We exclude from our measures of federally provided goods and services interest payments because they are not an expenditure valued by households, and income security (e.g., unemployment insurance and other welfare and social insurance benefits) because they are already included among transfers.

Figure P1 shows this measure of state and local spending on public goods and services scaled per state resident for our sample years.

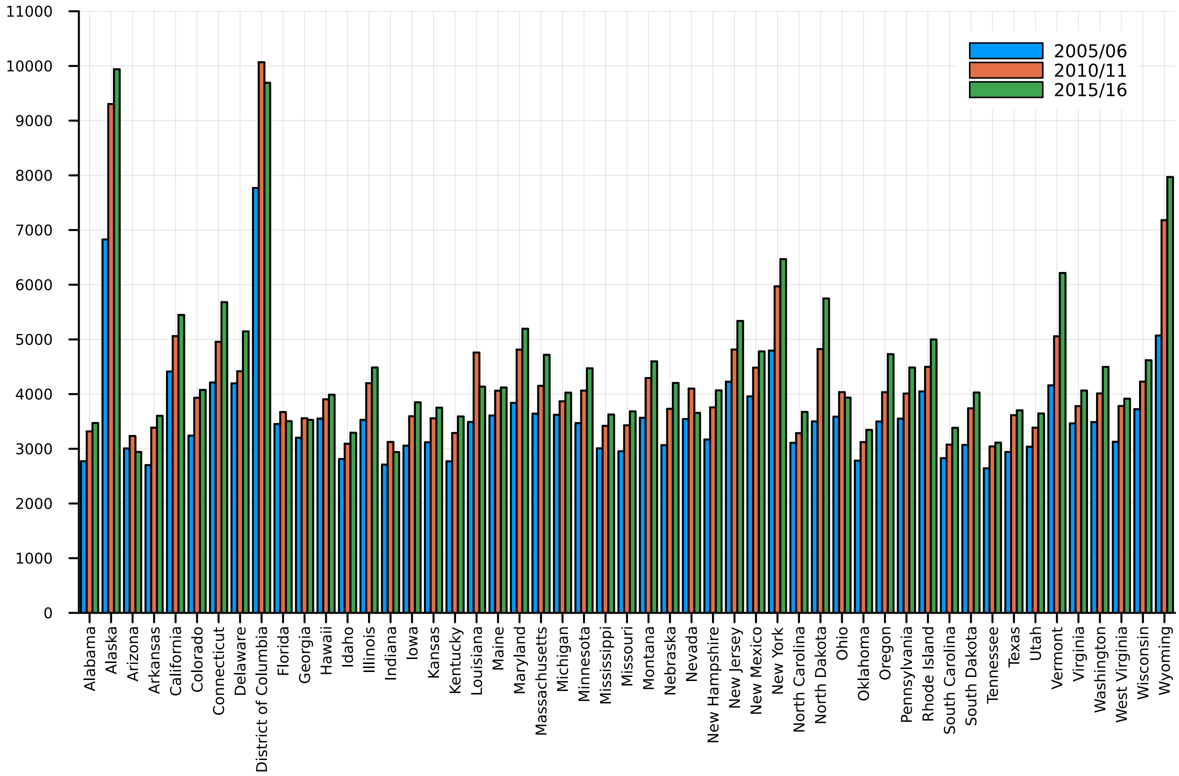

Figure P1: State and local spending on public goods and services per state resident per year, in current $. Computed from the augmented ASEC dataset using household weights. Population data are from the Census Bureau.

Q 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, 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.

Q.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 15). 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 Q1 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 (0.75).

Q.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

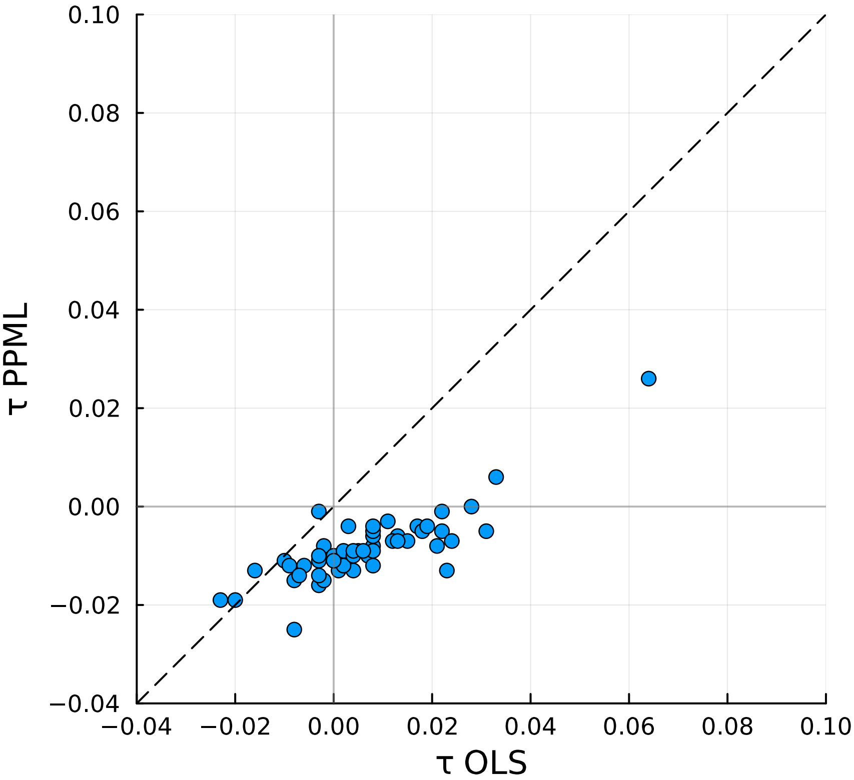

Figure Q1: State progressivity estimates for 2015/2016. For each state, the x axis value reports τ_s estimated by log OLS, while the y axis values reports τ_s estimated by PPML.

transfers, $y - T(y)$, is related to pre-government income y according to

$$y - T(y) = \lambda(y)^{1-\tau} + Tr, \tag{Q1}$$

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, 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.

Q.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).[124] 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.

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

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 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 N).

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.

References

AMORNSIRIPANITCH, N. (2020): "Why Are Residential Property Tax Rates Regressive?," Mimeo.

AUTEN, G., AND D. SPLINTER (2024): "Income Inequality in the United States: Using Tax Data to Measure Long-Term Trends," *Journal of Political Economy*, 132(7), 2179–2227.

AVENANCIO-LEÓN, C., AND T. HOWARD (2022): "The Assessment Gap: Racial Inequalities in Property Taxation," *Quarterly Journal of Economics*, 137(3), 1383–1434.

BAKER, S. (2024): "Property Tax Pass-Through to Renters: A Quasi-experimental Approach," Working Paper.

BERMAN, M., AND R. REAMEY (2016): "Permanent Fund Dividends and Poverty in Alaska," Working paper, Institute of Social and Economic Research, University of Alaska Anchorage.

BLEICH, S. N., A. J. MORAN, K. A. VERCAMMEN, J. M. FRELIER, C. G. DUNN, A. ZHONG, AND S. E. FLEISCHHACKER (2020): "Strengthening the Public Health Impacts of the Supplemental Nutrition Assistance Program Through Policy," *Annual Review of Public Health*, 41, 453–480.

BOAR, C., AND V. MIDRIGAN (2022): "Efficient Redistribution," *Journal of Monetary Economics*, 131, 78–91.

BOWMAN, J. B., D. A. KENYON, A. LANGLEY, AND B. P. PAQUIN (2009): "Property Tax Circuit Breakers: Fair and Cost-Effective Relief for Taxpayers," Policy Focus Report, Lincoln Institute of Land Policy.

BUCHMUELLER, T., J. C. HAM, AND L. D. SHORE-SHEPPARD (2015): "The Medicaid Program," in *Economics of Means-Tested Transfer Programs in the United States*, volume 1, edited by R. A. Moffitt, pp. 21–136. University of Chicago Press.

CENSUS BUREAU (2006): "Government Finance and Employment Classification Manual," .

——— (2015): *American Housing Survey*.

CENTER ON BUDGET AND POLICY PRIORITIES (2022): "The Supplemental Nutrition Assistance Program (SNAP)," Report.

CENTERS FOR MEDICARE & MEDICAID SERVICES (2020): "State Health Expenditure Accounts by State of Residence Highlights," Discussion paper.

CONGRESSIONAL BUDGET OFFICE (2015): "Federal Housing Assistance for Low-Income Households," Report.

CONGRESSIONAL RESEARCH SERVICE (2020): "Medicaid's Federal Medical Assistance Percentage (FMAP)," Report.

——— (2021): "Overview of the ACA Medicaid Expansion," Report.

DAVIS, A. (2018): "Property Tax Circuit Breakers in 2018," Policy Brief, Institute on Taxation and Economic Policy.

DAVIS, M. A., W. D. LARSON, S. D. OLINER, AND J. SHUI (2021): "The Price of Residential Land for Counties, ZIP Codes, and Census Tracts in the United States," *Journal of Monetary Economics*, 118, 413–431.

DELGADO, M., R. BRYDEN, AND S. ZYONTZ (2014): "Categorization of Traded and Local Industries in the US Economy," Mimeo.

DEPARTMENT OF HEALTH AND HUMAN SERVICES (2016): "Actuarial Report on the Financial Outlook for Medicaid," Report to Congress.

——— (2017): "Actuarial Report on the Financial Outlook for Medicaid," Report.

DOBRIDGE, C., P. LANDEFELD, AND J. MORTENSON (2021): "Corporate Taxes and the Earnings Distribution: Effects of the Domestic Production Activities Deduction," Finance and Economics Discussion Series 2021-081, Board of Governors of the Federal Reserve System.

DUSANSKY, R., M. INGBER, AND N. KARATJAS (1981): "The Impact of Property Taxation on Housing Values and Rents," *Journal of Urban Economics*, 10(2), 240–255.

ERNST & YOUNG (2016): "Total State and Local Business Taxes: State-by-State Estimates for Fiscal Year 2015," Report.

FERRIERE, A., P. GRÜBENER, G. NAVARRO, AND O. VARDISHVILI (2023): "On the Optimal Design of Transfers and Income-Tax Progressivity," *Journal of Political Economy Macroeconomics*, 1(2), 276–333.

Finkelstein, A., N. Hendren, and E. F. P. Luttmer (2019): "The Value of Medicaid: Interpreting Results from the Oregon Health Insurance Experiment," *Journal of Political Economy*, 127(6), 2836–2874.

Finkelstein, A., and R. McKnight (2008): "What Did Medicare Do? The Initial Impact of Medicare on Mortality and Out of Pocket Medical Spending," *Journal of Public Economics*, 92(7), 1644–1668.

Fleck, J. (2024): "Imputing Medicaid Transfers at the State Level," Working Paper.

Garner, T. I., G. Janini, L. Paszkiewicz, and M. Vendemia (2006): "The CE and the PCE: a comparison," *Monthly Labor Review*, 129, 20–46.

Guren, A. M., A. McKay, E. Nakamura, and J. Steinsson (2020): "Housing Wealth Effects: The Long View," *The Review of Economic Studies*, 88(2), 669–707.

Habib, B. (2018): "How CBO Adjusts for Survey Underreporting of Transfer Income in Its Distributional Analyses," Working Paper 2018-07, Congressional Budget Office.

Hahn, H., L. Aron, C. Lou, E. Pratt, and A. Okoli (2017): "Why Does Cash Welfare Depend on Where you Live? How and Why State TANF Programs Vary," Research Report, Urban Institute.

Hoo, S. (2005): "Property Tax Credits Offered Through State Income Tax Systems," Research Report, Tax Policy Center.

Hoynes, H. W., and D. W. Schanzenbach (2015): "US Food and Nutrition Programs," in *Economics of Means-Tested Transfer Programs in the United States*, volume 1, edited by R. A. Moffitt, pp. 219–302. University of Chicago Press.

Hoynes, H. W., and J. P. Ziliak (2018): "Increasing SNAP Purchasing Power Reduces Food Insecurity and Improves Child Outcomes," The Brookings Institution. https://www.brookings.edu/articles/increasing-snap-purchasing-power-reduces-food-insecurity-and-improves-child-outcomes/#:~:text=A%20central%20goal%20of%20SNAP,percent%20(6.4%20percentage%20points).

Hyman, D. N., and E. C. Pasour (1973): "Real Property Taxes, Local Public Services, and Residential Property Values," *Southern Economic Journal*, 39(4), 601–611.

Kaiser Family Foundation (2012): "Medicaid Financing: An Overview of the Federal Medicaid Matching Rate (FMAP)," Policy Brief.

Kline, P., N. Petkova, H. Williams, and O. Zidar (2019): "Who Profits from Patents? Rent-Sharing at Innovative Firms," *Quarterly Journal of Economics*, 134(3), 1343–1404.

König, J. (2023): "Bias in Tax Progresssivity Estimates," *National Tax Journal*, 76(2), 233–473.

Lamadon, T., M. Mogstad, and B. Setzler (2022): "Imperfect Competition, Compensating Differentials, and Rent Sharing in the US Labor Market," *American Economic Review*, 112(1), 169–212.

Langley, A. H. (2015): "Estimating Tax Savings from Homestead Exemptions and Property Tax Credits," Working Paper WP15AL1, Lincoln Institute of Land Policy.

Larrimore, J., J. Mortenson, and D. Splinter (2021): "Household Incomes in Tax Data: Using Addresses to Move from Tax Unit to Household Income Distributions," *Journal of Human Resources*, 56(2), 600–631.

Levinson, A. (2021): "America's Regressive Wealth Tax: State and Local Property Taxes," *Applied Economics Letters*, 28(14), 1234–1238.

Lincoln Institute of Land Policy and George Washington Institute of Public Policy (2024): "State-by-State Property Tax at a Glance," .

Lincoln Institute of Land Policy and Minnesota Center for Fiscal Excellence (2018): "50-State Property Tax Comparison Study: For Taxes Paid in 2017," .

McCluskey, W.J., G. C. Cornia, and L. C. Walters (eds.) (2012): *A Primer on Property Tax: Administration and Policy*. Wiley.

McMillen, D., and R. Singh (2020): "Assessment Regressivity and Property Taxation," *Journal of Real Estate Finance and Economics*, 60(1-2), 155–169.

Medicaid and the CHIP Payment and Access Commisson (2017): "Report to Congress on Medicaid and CHIP," Report.

——— (2018a): "Fact Sheet: State Children's Health Insurance Program (CHIP)," Discussion paper.

——— (2018b): "MACStates: Medicaid and CHIP Data Book," .

MILLER, A. C. (1893): "On Incidence of Taxation," *Journal of Political Economy*, 1(3), 444–468.

MINNESOTA DEPARTMENT OF REVENUE, TAX RESEARCH DIVISION (2024): "2024 Minnesota Tax Incidence Study: An Analysis of Minnesota's Household and Business Taxes," Report.

MOEHLING, C. M. (2007): "The American Welfare System and Family Structure: An Historical Perspective," *Journal of Human Resources*, 42(1), 117–155.

NATIONAL ASSOCIATION OF COUNTIES (2010): "Property Taxes: A Look at Exemptions, Tax Limits and Assessment Cycles," Discussion paper.

NATIONAL ASSOCIATION OF STATE BUDGET OFFICERS (2017): "State Expenditure Report: Examining Fiscal 2015-2017 State Spending," .

OATES, W. E., AND W. A. FISCHEL (2016): "Are Local Property Taxes Regressive, Progressive, or What?," *National Tax Journal*, 69(2), 415–434.

PADGITT, K. (2009): "Updated State and Local Option Sales Tax," Fiscal Fact 196, Tax Foundation.

PELLETIERE, D., M. CANIZIO, M. HARGRAVE, AND S. CROWLEY (2008): "Housing Assistance for Low Income Households: States Do Not Fill the Gap," Report, National Low Income Housing Coalition.

PIKETTY, T., E. SAEZ, AND G. ZUCMAN (2018): "Distributional National Accounts: Methods and Estimates for the United States," *Quarterly Journal of Economics*, 133(2), 553–609.

SCHNEIDER, A., R. ELIAS, AND R. GARFIELD (2002): "Medicaid Eligibility," in *The Medicaid Resource Book*, edited by A. Schneider, pp. 3–48. The Kaiser Commission on Medicaid and the Uninsured.

SCHNEIDER, A., AND R. GARFIELD (2002): "Medicaid Benefits," in *The Medicaid Resource Book*, edited by A. Schneider, pp. 49–80. The Kaiser Commission on Medicaid and the Uninsured.

SCHNEIDER, A., AND D. ROUSSEAU (2002): "Medicaid Financing," in *The Medicaid Resource Book*, edited by A. Schneider, pp. 81–128. The Kaiser Commission on Medicaid and the Uninsured.

SCHOTT, L., L. PAVETTI, AND I. FLOYD (2015): "How States Use Federal and State Funds Under the TANF Block Grant," Report, Center for Budget and Policy Priorities.

SERRATO, J. C. S., AND O. ZIDAR (2016): "Who Benefits from State Corporate Tax Cuts? A Local Labor Markets Approach with Heterogeneous Firms," *American Economic Review*, 106(9), 2582–2624.

SILVA, J. M. C. S., AND S. TENREYRO (2006): "The Log of Gravity," *Review of Economics and Statistics*, 88(4), 641–658.

SNYDER, L., R. RUDOWITZ, R. GARFIELD, AND T. GORDON (2012): "Why Does Medicaid Spending Vary across States: A Chart Book of Factors Driving State Spending," Issue Paper, Kaiser Family Foundation.

SUPER, N. (2003): "The Geography of Medicare: Explaining Differences in Payment and Costs," Issue Brief 792, National Health Policy Forum.

TSOODLE, L. J., AND T. M. TURNER (2008): "Property Taxes and Residential Rents," *Real Estate Economics*, 36(1), 63–80.

WALCZAK, J. (2019): "Local Income Taxes in 2019," Fiscal Fact 667, Tax Foundation.

ZILIAK, J. P. (2015): "Temporary Assistance for Needy Families," in *Economics of Means-Tested Transfer Programs in the United States*, volume 1, edited by R.A. Moffitt, pp. 303–394. University of Chicago Press.