Income Insurance in the Fifty Nifty: Evidence from America's Working Poor*

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Abstract

This paper explores how income support for working poor households varies across US states. We overcome limitations in survey data by approximating the lower tails of state income distributions and by building an imputation model which measures the combined response of federal and state income taxes and transfers to changes in earnings. Our imputations account for the geographic uniformity of federal policies as well as regional variation in income distributions, price levels and net transfer policies of state governments. We find large geographic differences in cumulative marginal tax rates and show that these differences materialize as variation in public insurance against transitory earnings shocks; their pass-through to disposable income ranges from 30 to 90%. Cross-state differences remain after adjusting for the local purchasing power of tax credits and transfers. States with higher shares of Black residents and lower mean incomes provide less insurance while those with income taxes, higher price levels and more Democrat leaning voters provide more.

Keywords: Taxes and Transfers, State and Local Taxes, Poverty, Income Distribution

JEL Classification: H2, H7, I3, D3

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1 Introduction

Measuring the marginal tax rates faced by low-income American households is a challenge. Despite efforts to oversample them, this population is underrepresented in household surveys. Moreover, a substantial part of their incomes is provided by tax credits and transfers. Thus, as low-income households usually participate in several of these programs simultaneously, measures of their marginal tax rates need to be *cumulative*. Furthermore, self-reported information on transfers is known to be contaminated by measurement error; it underestimates both the number of recipients as well as the value of the transfers received.[1]

In addition, most transfer programs have state options so state governments have numerous ways to customize the American social safety net.[2] Besides this, some states provide earned income and child tax credits. As a result, there is substantial cross-state dispersion in the eligibility for and generosity of support programs for low-income households. Also, federal earned income tax credits and transfers are uniform in nominal terms. Hence, regional disparities in price levels lead to a spatial distribution of purchasing power adjusted marginal tax rates.[3]

In this paper, we provide quantitative measures of state-specific marginal tax rates for low income households and show that they determine the share of transitory earning shocks passed to disposable income. To address limitations in survey data, we construct an imputation model which provides household-level measures of state and federal taxes and transfers. Throughout our analysis, we aim to capture as many dimensions of cross-state variation as possible, i.e. we split marginal tax rates into federal and state contributions, paying particular attention to state income tax systems. Moreover, for federally mandated programs with state options such as TANF, Medicaid and CHIP, we attribute contributions using federal and state funding shares.

A cornerstone of our work is the use of publicly available survey data to carefully approximate the lower tails of state income distributions. We do so as it is well-established that the variability of disposable income (i.e. income *after* taxes and transfers) increases as earned income falls. Consequently, popular parametric estimates of the relationship between earned income and marginal tax rates are ill-suited for low incomes. For example, as figure 1 illustrates, the simple parametric relationship between log pre-government (taxable) income and marginal tax rates captured by the tax function of Heathcote, Storesletten, and Violante (2017) is misspecified for low incomes.[4]

[1] As illustrated by Meyer, Mok, and Sullivan (2009), Wheaton (2008) and others, this problem is present even in dedicated surveys such as the Survey of Income and Program Participation (SIPP). One reason is that the value of transfers provided in kind can be unknown to recipients.

[2] Three prominent transfer programs with state options are Temporary Assistance for Need Families (TANF), Medicaid and the Childrens Health Insurance Program (CHIP). TANF alone has so many state options regarding eligibility and generosity that each state can be considered as having "its own unique TANF program" (Hahn et al. (2017), p. 6).

[3] Appendix A provides summary measures of cross-state price dispersion and outlines further relevant dimensions of state heterogeneity.

[4] This limitation also applies to other parametric tax functions; as documented by Guner, Kaygusuz, and Ventura (2014), these functions generally have a poor fit for low incomes.

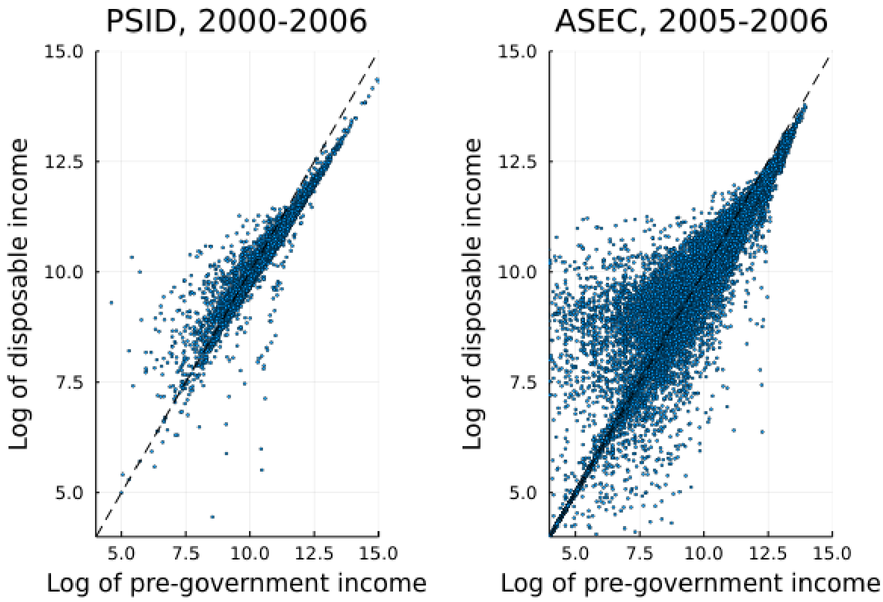


Figure 1: *Household log pre-government income and disposable income in survey data. Variable definitions as in Heathcote, Storesletten, and Violante (2017).*

We also account for the role of regional price level differences in determining the real value of state and federal assistance programs. This aspect is especially relevant for federal programs as they are fixed in nominal terms. But it is also crucial to determine the *real* value of support provided from state governments. To this end, we construct a year and state specific price. In particular, as opposed to a general price level measure, our measure refers to the prices of expenditures which represent the majority of low-income households' consumption spending, namely food and housing.

Our imputation model accurately replicates the dispersion of marginal tax rates among low income households and documents systematic geographic variation. This variation is driven by differences in state income distributions, prices levels and policies. Moreover, we find that demographic features of low income households (marital status and number of dependents in particular), are key determinants of marginal tax rate heterogeneity. Higher marginal tax rates imply a *lower* elasticity of disposable income with respect to earned income (for a given level of earned income). Thus, states in which households face higher marginal tax rates – either federal or state – receive more insurance against negative earnings shocks. Since low-income households generally have little or no liquid assets for self-insurance, our findings on variation in public insurance have implications for the regional transmission of shocks to consumption spending. Finally, we establish that the state's political tilt, the price level, the share of black residents and the existence of a state income tax are significant determinants of earnings insurance in each state.

The remainder of this paper is organized as follows: In section 2, we benchmark our paper against the existing research on income insurance in the American welfare system and tax progressivity. In section 3, we describe the details of our imputation model which captures the responses of federal and state net transfers to changes in pre-tax income. Section 4 presents our main results and section 5 studies which state-level characteristics correlate with the levels of progressivity we find. Section 6 concludes.

2 Related Literature

Our paper contributes to the literature on income insurance provided by various national tax and transfer programs. A study closely related to ours is Grant et al. (2010) who support our emphasis on the effect of state tax policies on disposable incomes as they find a negative correlation between state redistributive taxation and the standard deviation of a state's consumption distribution. Using data from the Panel Study of Income Dynamics (PSID), Hoynes and Luttmer (2011) evaluate the welfare impact of US state tax and transfer programs, decomposing it into a redistributive and an insurance component. While their research question is similar to ours, their data to not allow them to include all states in their analysis or concentrate on low-income households with different demographic structures. In terms of methodology, our paper is close to Dolls, Fuest, and Peichl (2012) who use a microsimulation to compare the automatic stabilizers of US states and 19 European countries. Mok, Holtzblatt, and Sammartino (2012) compute effective marginal tax rates (EMTRs) for low and moderate incomes and considers the effects of eligibility cutoffs as well as phase-in and phase-out thresholds of different transfer programs.

A key feature of all these papers is that in principle they study the entire national population. Thus, they average across state differences and do not consider systematic geographic heterogeneity. These studies also do not provide a granular analysis of low income households and do not distinguish between different household demographics (such as the age and number of dependents or the household's tax filing status).

Our paper, instead, focuses on low income households with different demographic characteristics residing in different states. In this respect, we are close to Maag et al. (2012) who find large differences in EMTRs, depending on the state of residence and the pattern of earnings throughout the year. The sensitivity of EMTRs at low incomes is further substantiated by Kosar and Moffitt (2017), who focus on the role of household demographics and participation in different sets of welfare programs. Our results complement these earlier studies as our imputation model allows us to study EMTRs corresponding to arbitrary changes in earnings. Thus, contrary to these papers, we do not focus on hypothetical earnings changes but compute EMTRs corresponding to changes which are empirically relevant for low-income households.

Another strand of research evaluates spatial distortions caused by the (nominal) uniformity of federal policies – a key mechanism studied by our analysis. For example, Kaplow (1995) and Glaeser (1998) investigate if the US federal tax system should account for regional differences in the cost of living. Albouy (2009) finds that workers with the same real income pay higher federal income taxes in high-cost areas. His simulation suggests that the resulting incentives to relocate to low-cost areas have lowered employment, house prices and land values in high-cost areas. These and related findings have been a starting point for proposals to target federal policies regionally. For instance, Ziliak (2016), Hoynes and Ziliak (2018) and Bronchetti, Christensen, and Hoynes (2019) propose adjusting Food Stamps (SNAP) benefits to account for geographic variation in food prices. Finally, Austin, Glaeser, and Summers (2018) propose targeting pro-employment policies towards regions with high rates of long-term unemployment to address diverging regional living standards.

Finally, our empirical characterization of marginal tax rates contributes to an extensive literature on measuring tax progressivity and its optimal level. Kaplan and Violante (2010), McKay and Reis (2016) and Heathcote, Storesletten, and Violante (2017) contributed widely-cited analytical frameworks demonstrating that tax progressivity matters for macroeconomic stabilization, labor supply decisions, human capital investments and consumption insurance. However, as illustrated earlier, the simple parametric measures of tax progressivity used by these papers are appropriate for middle and high income earners but not for low-income households. Moreover, papers in this literature generally abstract from regional tax progressivity variation and so cross-state variation in EMTRs is absent in recent work on estimating tax functions with household demographics, such as DeBacker, Evans, and Phillips (2019), the response of the US safety net to the business cycle, for example Bitler, Hoynes, and Iselin (2020), or introducing a Universal Basic Income, Guner, Kaygusuz, and Ventura (2021).[5] Our work shows that this approach omits a relevant dimension of heterogeneity, especially as the dispersion of EMTRs is most pronounced at the lower end of the income distribution.

3 Imputation Model

In this section, we provide details on our imputation model and the calculations we perform with it. We also describe the three prototype families which we consider as our households of interest. The basic idea of our imputation exercise is this: In a given year, we place a prototype family in each US state at a given level of pre-tax earnings. We then reduce this pre-tax income by a given amount and calculate the relative change in disposable income which results from the change in federal and state taxes and transfers. In our baseline exercise, we include federal and state income taxes as well as those transfers which are generally identified with the US welfare system, i.e. Temporary Assistance to Needy Families (TANF) and Food Stamps (SNAP). In addition, we adjust the results to account for state specific prices. In an extension, we also include the Medicaid transfer program .

3.1 Measuring Marginal Tax Rates and Insurance

In an ideal setting, estimating measures of cumulative marginal tax rates would require household level panel data on earnings, taxes, transfers and family demographics. To see this, consider the budget equation of a low-income, hand-to-mouth (zero savings) household i at time t in state s

$$y^d_{i,t,s} = y_{i,t,s} + g^s_{i,t,s} + g^f_{i,t,s} - \tau^s_{i,t,s} - \tau^f_{i,t,s} \tag{1}$$

[5] One novel exception is Fleck et al. (2021) who measure the combined progressivity of state taxes across a wide range of instruments, including consumption and property taxes.

where y^d denotes disposable and y earned income while g^f (g^s) and τ^f (τ^s) are federal (state) transfers and taxes.[6] The marginal rate of any tax or transfer program k, g_k or τ_k, mtr_k describes the change in this program's liability (the 'liability' being negative for a transfer) as earned income increases by an infinitesimal amount so that

$$\mathrm{mtr}_{\tau_k} = \left.\frac{d\tau_k}{dy}\right|_{i,t,s} \tag{2}$$

If $\mathrm{mtr}_k > 0$ the tax or transfer is commonly called progressive and regressive otherwise, although these characterizations may not be fully accurate if we consider the full schedule of tax rates as a function of income. The cumulative mtr corresponding to participation in multiple tax and transfer programs is equal to the sum of each program's mtr.[7] [8] Effective tax rates are especially large when households *lose* or *gain* eligibility to a specific program. This effect is compounded as several programs have similar eligibility cutoffs. This phenomenon is well-documented in, for example, Maag et al. (2012) and Kosar and Moffitt (2017).

Even access-restricted datasets do not provide sufficient information to provide empirical estimates of the derivative shown in equation (2). In a number of papers Guvenen, Song and coauthors use administrative data provided by the Social Security Administration from W2 forms which contains detailed information on reported earnings.[10] However, these data do not contain any measures for taxes or transfers, nor do they allow linking members of the same household. Thus, while useful for studying changes in labor earnings over time, they cannot be used to measure the corresponding changes in taxes and transfers. Similarly, Chetty and coauthors use information reported on 1040 forms provided by the Internal Revenue Service's Statistics of Income (SOI).[11] Yet, these forms do not contain information on transfers received. Therefore, they are unsuitable for our research objective which requires earnings, tax and transfer information from the same household unit over several years. In addition, we require a large number of households per state to identify cross-state variation in marginal taxes.

As we are unable to meet these data requirements, we resort to a carefully specified imputation model to measure marginal tax rates, i.e. for a given state of residence, household composition

[6] We suppress notation referring to the demographic characteristics of the household, which determine eligibility for welfare programs and income tax credits. As we study three different types of households, we hold these characteristics fixed for each of them during our analysis.

[7] For the representation shown in equation (1), the cumulative marginal tax rate MTR is given as

$$MTR = \frac{d\tau^s}{dy} + \frac{d\tau^f}{dy} - \frac{dg^s}{dy} - \frac{dg^f}{dy} \tag{3}$$

[8] Note that in practice neither taxes nor transfers are continuous in income. The reason is twofold. First, eligibility and amounts are determined using statutory (nominal) cutoffs.[9] For low income households, the fixed nominal thresholds of the Earned Income Tax Credit (EITC) are especially relevant. As shown in appendix C, a household's EITC marginal tax rate can abruptly change from negative (phase-in) to zero (maximum EITC) or positive (phase-out) for small changes in pre-tax income. Second, marginal tax rates are also determined by characteristics such as household composition and tax filing status. These factors receive more attention in the policy design of transfer programs but are also consequential in determining income taxes, e.g. through sizable differences in standard deductions and exemptions.

[10] Examples are Guvenen, Ozkan, and Song (2014), Guvenen et al. (2017) and Guvenen et al. (2021).

[11] Examples are Chetty et al. (2014) and Chetty and Hendren (2018).

and income, we impute taxes and transfers. This approach allows us to impute changes in taxes and transfers as income changes while holding other characteristics fixed. In addition, we can impute changes in net transfers for arbitrary earnings changes and obtain precise estimates of policy specific rates mtr_k as well as the cumulative tax rate MTR.

As cumulative marginal tax rates reflect the elasticity of net transfers with respect to changes in earned income, they are also measures of the insurance capacity of the tax and transfer system. To see this, define net taxes as $T_t = \tau_t - g_t$ where T may be negative (reflecting a credit), zero or positive (reflecting a liability). Further, assume a dynamic perspective with discrete time so that, after taking time differences, dynamic changes in the household budget can be written as

$$y^d_{i,t+1,s} - y^d_{i,t,s} = y_{i,t+1,s} - y_{i,t,s} - (-T^s_{i,t+1,s}) - T^s_{i,t,s} - (-T^f_{i,t+1,s}) - T^f_{i,t,s} \tag{4}$$

$$\Delta y^d_{i,s} = \Delta y_{i,s} - \Delta T^s_{i,s} - \Delta T^f_{i,s} \tag{5}$$

where Δy_i represents an exogenous change in earnings while ΔT^f_t and ΔT^s_t are endogenous changes in net state and federal taxes. Accordingly, changes in disposable income, Δy^d_i are partly determined by the response of net taxes. To emphasize that changes in earnings are driven by shocks in our framework, let $\Delta y_i = \varepsilon_{t,i}$. Thus, if changes in net transfers are such that

$$\Delta T^s_{i,s} + \Delta T^f_{i,s} = \varepsilon_{i,s} \implies \Delta y^d_{i,s} = 0 \tag{6}$$

taxes and transfers provide perfect insurance as the pass-through of the earnings shock to disposable income is zero.

Tax and transfer systems with strictly positive MTRs provide insurance while systems with negative MTRs exacerbate shocks. This property of tax and transfer systems is especially relevant for low-income households, which generally have little or no access to private insurance in the form of precautionary savings. Therefore, these households are forced to absorb any unsmoothed shocks by adjusting their consumption expenditures.[12] To measure the on-impact response of tax and transfers to changes in individual earnings, we compare changes in disposable incomes to the size of the earnings shock. Using the notation introduced earlier, pre-tax income after receiving the shock is given by

$$y_{i,t+1,s} = y_{i,t,s} + \varepsilon_{i,s} \tag{7}$$

The pre-shock and post-shock disposable incomes, $y^d_{i,t+1,s}$ and $y^d_{i,t,s}$ can be computed using

$$y^d_{i,t,s} = y_{i,t,s} - \tau^f(y_{i,t,s}) - \tau^s(y_{i,t,s}) + g^f(y_{i,t,s}) + g^s(y_{i,t,s}) \tag{8}$$

$$y^d_{i,t+1,s} = y_{i,t+1,s} - \tau^f(y_{i,t+1,s}) - \tau^s(y_{i,t+1,s}) + g^f(y_{i,t+1,s}) + g^s(y_{i,t+1,s}) \tag{9}$$

where all right hand side variables (except y) have been imputed as they are functions of $y_{i,t,s}$

[12]This link between changes in consumption and changes in disposable income can also be derived by assuming that middle or high income households are liquidity constrained, i.e. belong to the "wealthy hand-to-mouth" using the terminology of Kaplan, Violante, and Weidner (2014).

and $y_{i,t+1,s}$. Using the disposable incomes computed in this way, our measure of the insurance provided by the tax and transfer system in state s for year t and individual i is given as

$$\chi_{i,t,s} = 1 - \frac{y^d_{i,t+1,s} - y^d_{i,t,s}}{y_{i,t+1,s} - y_{i,t,s}} \tag{10}$$

$$= \frac{\Delta g^f(y_{i,t+1,s}) + \Delta g^s(y_{i,t+1,s}) - \Delta \tau^f(y_{i,t+1,s}) - \Delta \tau^s(y_{i,t+1,s})}{\varepsilon_i} \tag{11}$$

where $\Delta x(y_{i,t+1,s}) = x(y_{i,t+1,s}) - x(y_{i,t,s})$ for $x \in \{\tau^f, \tau^s, g^f, g^s\}$.

If disposable income declines by the entire amount of the shock ε, the insurance measure χ will be zero, indicating that the system provides no insurance. Conversely, if disposable income does not decline at all, χ will be one, indicating full insurance. Intermediate values indicate partial insurance.[13] In other words, χ is a non-parametric measure for how much of the shock is passed through to disposable income so it can be interpreted as the percentage of the shock which is publicly insured. Note that χ is not bounded into the open unit interval; it can be negative, indicating that the response of taxes and transfers *exacerbates* the earnings shock so that disposable income falls by more than the shock. If it is greater unity, the system *overcompensates* for the fall in earnings so that disposable income is larger after than before the shock.

Moreover, note that χ is additively separable so we can define $\chi_{i,t,s} = \chi^f_{i,t,s} + \chi^s_{i,t,s}$ where

$$\chi^f_{i,t,s} = \frac{\Delta g^f(y_{i,t+1,s}) - \Delta \tau^f(y_{i,t+1,s})}{\varepsilon_i} \tag{12}$$

$$\chi^s_{i,t,s} = \frac{\Delta g^s(y_{i,t+1,s}) - \Delta \tau^s(y_{i,t+1,s})}{\varepsilon_i} \tag{13}$$

This illustrates that we can separately identify the individual insurance contributions of federal and state taxes and transfers. Finally, χ is similar to popular measures of tax progressivity as it relates variation in earned income to variation in disposable income. However, it is conceptually distinct; it measures the capacity of taxes and transfers to offset *level changes* in earned income. To see this, consider the role of the payroll (FICA) tax in providing insurance against a fall of earned income equal to \$100. Even though payroll taxes are regressive (their rate is independent of earned income and subject to an assessment limit), χ attributes a positive contribution as the FICA tax liability falls by a positive amount so[14]

$$\chi^{FICA} = \frac{100 \times 15.3\%}{100} = 0.153 > 0 \tag{14}$$

In the following two sections, we explain how we compute $\chi_{i,t,s}$ and its decomposition for each state and year from 2000 to 2007. To do so, we exhibit the critical inputs and elements of the model such as earned incomes y, family types i, taxes τ, transfers g and shocks ε. Finally, note that χ also allows an analogous interpretation in real terms; specifically, after dividing the

[13] Thus, our measure allows the same interpretation as the 'partial insurance coefficient' presented by Blundell, Pistaferri, and Preston (2008) but estimating it has much less comprehensive data requirements.

[14] 15.3% = 12.4% + 2.9% (employer and employee portions of OASDI and Medicare taxes)

nominal shock ε and the changes in taxes and transfers by a measure of living costs in each state and year, we can measure the *real* value of the insurance provided by each level of government. We explain this adjustment in section 3.4.

3.2 Prototype Tax Filers

We consider three different types of households and keep their characteristics fixed across years and states. Fixing these characteristics allows a clean comparison of the marginal tax rates and the insurance quality of each state's social safety net. If instead we were to vary the family composition between states and years to reflect state averages, we would not be able to separate the effects of federal and state policies consistently.

Other than income, the most relevant household characteristic determining taxes is the tax filing status and the number of dependents claimed by the tax filer. Both determine exemptions, general deductions, child tax credits and specific deductions such as childcare expenses. Moreover, the number of family members is a critical parameter for SNAP and TANF eligibility and generosity. For Medicaid, a key element of the heterogeneity in eligibility across states is the extent to which children are covered. Thus, to provide a comprehensive assessment, we study three prototype households: first, a married couple with two children filing jointly ('Miller' family). Second, a single parent with two children filing as head of household ('Jones' family). And third, a childless single tax filer ('SF').

Household composition For all three prototype households, we assume that no family member has any disability and that no other family members are present in the household residence. Moreover, we assume that the family home is rented (i.e. they do not make any mortgage interest payments, which could be deducted from taxes). We also fix the ages of adults and children (if present). Table 1 shows a summary of these characteristics for each prototype household.

	Miller	**Jones**	**SF**
Head Age	31	31	31
Spouse Age	29	na	na
Number of Children	2	2	0
Children Ages	4, 5	4, 5	na
Tax Filing Status	Joint, married	Head of Household	Single

Table 1: *Demographics and tax filing status of prototype families*

Earned Incomes For all three prototype households, we assume that earned income is wage and salary income only. For the married joint filer household, we assume that both spouses earn the same amounts. Since our population of interest are the working poor, we draw the household's initial earned income from the first to the twentieth percentile of state and year specific income distributions. We generate measures of the first 20 percentile values using parametric (lognormal) approximations of the empirical distributions referring to the three prototype households. We compute the moments of these distributions using data from the American Community Survey (ACS). In addition, we use data from the Current Population Survey (CPS) Earner Study to calculate minimum earnings amounts which we apply to truncate the income distributions from below. Appendix G provides more details in our procedure, including table 8 which shows the mean as well as first and twentieth percentile values of the earnings of each prototype family by state for 2005. This appendix also presents summary statistics of relevant household attributes such as age, educational attainment and race, for the ACS samples from which we compute the earned income distribution moments.

3.3 Taxes and Transfers

For all programs included in our imputation model, we assume a take up of 100%.[15] This allows us to measure statutory rates without the confounding effect of varying participation behavior. Thus, our results measure upper bounds for support received by low income households and capture the system in its most generous form.

Federal and State Income Taxes We use TAXSIM to impute federal and state income taxes owed (or credits earned), including the EITC and social security (FICA or "payroll") taxes.[16] For the social security taxes, we only consider the employer portion. TAXSIM carefully models income taxes for a number of input variables, including tax filer demographics. Throughout this exercise, we assume that the prototype households have zero capital and business incomes. Moreover, we assume that they have no deductible expenses separating gross income and adjusted gross income (AGI). The relevance of this point is discussed in Appendix C.

Transfers In our baseline exercise, we consider the transfer programs SNAP and TANF; in an extension we also include Medicaid. We choose to deal with Medicaid separately because it insures low-income households against health expenditure shocks (as opposed to pure earnings risk). With the exception of TANF, all of the other transfer programs can be considered in kind and we work with their full cash value.[17] Our imputation methodology for the transfer programs is explained in Appendix D and table 2 summarizes all taxes and transfers our model considers as well as their funding sources and the relative magnitudes.

[15]This assumption implies that households file taxes to take advantage of the EITC and CTC even if they are below the filing threshold.

[16]We abstract from local income taxes because they are levied by a very small number of local governments and are quantitatively minor.

[17]The importance of in kind transfers for household insurance is illustrated in, for example, Gadenne et al. (2021).

Tax and Transfer Programs	Expenditures (2007 USD)		Imputation
	total (bn)	recipient/month	
FEDERAL FUNDING			
Supplemental Nutrition Assistance Program (SNAP, 'Food Stamps')	30	96	Calculator (Appendix D)
Earned Income Tax Credit (EITC)	49	165	TAXSIM
FEDERAL-STATE FUNDING			
Temporary Assistance for Needy Families (TANF, formerly AFDC)	12	234	Calculator (Appendix D)
Medicaid	329	482	Calculator (Appendix D)
STATE FUNDING			
State Earned Income Tax Credit (SEITC)	n/a	n/a	TAXSIM
Unemployment Insurance (UI)	32	354	Calculator (Appendix E)

Source: Ben-Shalom, Moffitt, and Scholz (2011)

Table 2: *Tax and transfer programs included in our imputation model*

3.4 State Price Measure

To capture the state specific purchasing power of transfers and tax credits, we convert nominal USD amounts into comparable consumption units by constructing a 'subsistence expenditure basket'. We calculate the price of this basket as the sum of two components. The first is the minimum required level of monthly food spending as specified by the federal Thrifty Food Plan.[18] The second is the average monthly rent payment for low income households in a given state and year. We scale this measure so it refers to one month of expenditures.

We construct the subsistence basket in this way because food and rent make up a substantial portion of total consumption spending for low-income households; according to data from the Consumer Expenditure Survey (CE), their combined spending share is greater than 50%. In addition, this price measure focuses on necessities, i.e. expenditures which cannot be substituted in response to a fall in earnings. Thus, from an insurance perspective, these appear to be the most relevant spending categories. For the same reason, we exclude expenditures on durable goods. Appendix F lists the state specific nominal values of the baskets (averaged over years) and describes the data sources used to construct them.

Note that food is generally exempt from (state) sales taxation. However, as shown in figure 2, rents do reflect differences in mean state property taxes to some extent.[19] Thus, while our analysis focuses on income taxes levied by state governments, we capture cross-state differences in property taxes via prices of the subsistence basket.

[18]The Thrifty Food Plan is a measure provided by the US Department of Agriculture. It specifies the minimum amount which a family of a given size needs to spend to consume a nutritious diet. As such, it is an important parameter in the SNAP program.

[19]In fact, studies such as Tsoodle and Turner (2008) report a high pass-through of property taxes to rents.

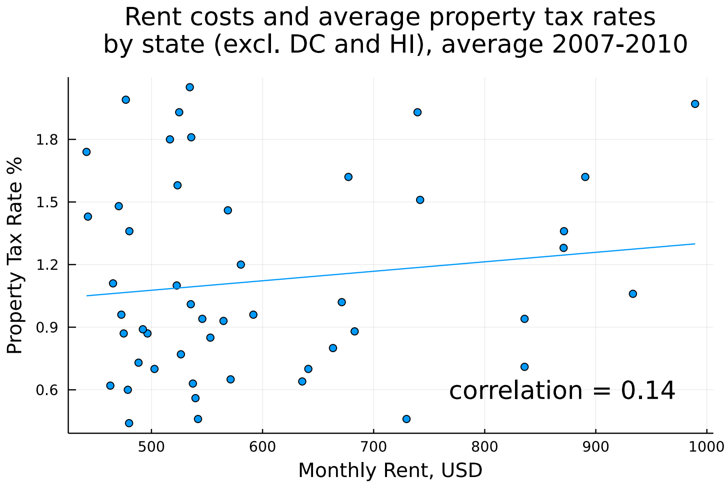


Figure 2: *Relationship between mean state property tax rates and rents paid by low income households*

In summary, state (and year) specific prices introduce another dimension of heterogeneity in our estimates of the insurance measure presented above. This can easily be seen from equations (8) and (9); dividing the right hand side terms by state (and year) specific prices leads to different real values of each tax and transfer program.

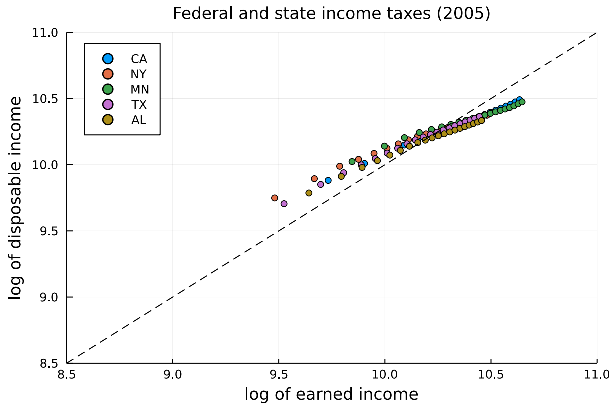
4 Results

4.1 Dispersion of Disposable Incomes

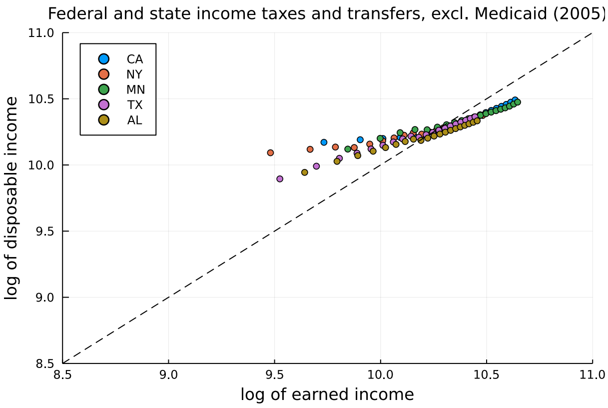
As a first inspection, figures 3 to 5 show the dispersion of (log) disposable incomes our imputation model produces for the three different prototype households. Panels (a) illustrate imputed federal and state income taxes while panels (b) also include SNAP and TANF transfers which are contained in our baseline analysis.[20] Section H.1 in the appendix shows analogous results for an extension in which we also include the Medicaid and CHIP transfer programs. For ease of exposition, the panels illustrate results for the year 2005.[21]

[20] As in Heathcote, Storesletten, and Violante (2017), figure 1 includes deductions and the employer share of FICA in pre-government and disposable income. However, the figures in this section plot logs of earned and disposable incomes without considering deductions. This illustration facilitates comparing income *levels* and these income definitions relate more directly to our price measures.

[21] Results are very similar for other years between 2000 and 2007.

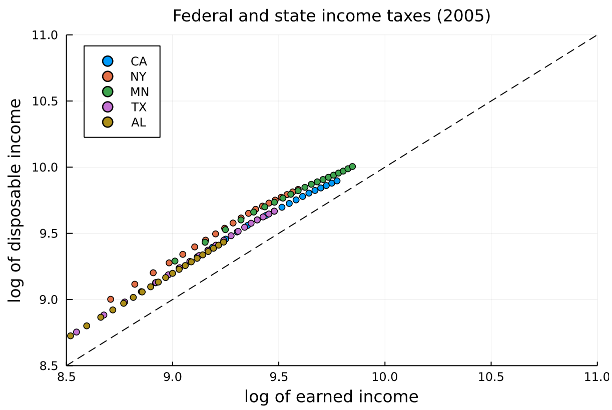


(a) Income taxes

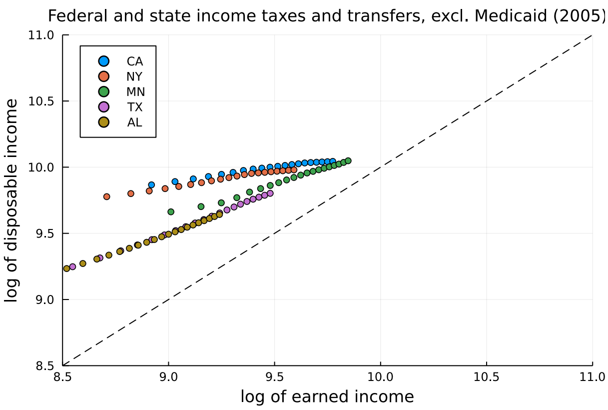


(b) Income taxes and transfers

Figure 3: *Miller Family*

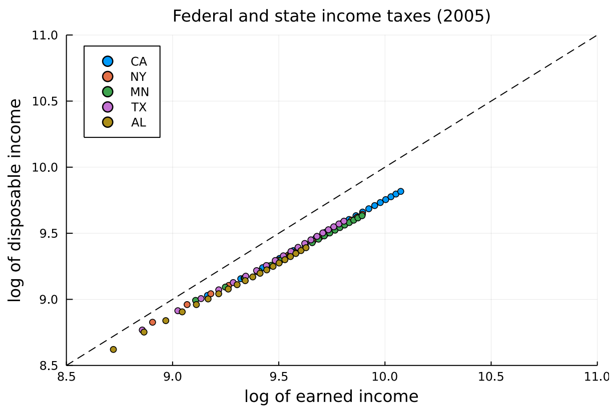


(a) Income taxes

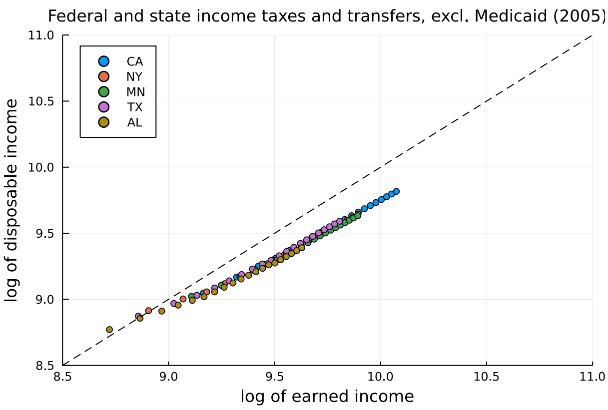


(b) Income taxes and transfers

Figure 4: *Jones Family*



(a) Income taxes



(b) Income taxes and transfers

Figure 5: *Single Filer*

The figures illustrate that several dimensions of cross-state heterogeneity drive the dispersion of disposable incomes. First, each point in these figures represents one of the lowest 20 income percentiles. Thus, horizontal differences between prototype households reflect discrepancies in their earned incomes. For a given type of household, they reflect cross-state income discrepancies. For example, for the married tax filer ("Miller Family"), the 20th percentile of Alabama is equivalent to the eleventh percentile in California and Minnesota. This is because incomes of this type of household in Alabama are (much) lower than in the other two states.

Second, for a given amount of earned income, vertical disposable income differences are driven by state taxes and transfers. Thus, they are a direct measure of state income tax systems as federal taxes are determined entirely by nominal earned incomes. For instance, panel (a) of figure 3 shows that, in Minnesota, Miller type households become net tax payers starting from around $30,000. In Alabama, this number is about $24,000. The household head tax filer household ("Jones Family") is never a net tax payer while the single filer ("Single Filer") always is – even though their earned income values are similar in all states. This discrepancy is due to the favorable treatment of children which allow to claim dependent deductions as well as larger amounts of earned income tax credits and child tax credits provided by the federal and some state income tax systems.

Panels (b) show that including transfers increases the dispersion in marginal tax rates even more. This finding applies to the married and household head filers in particular. For the former type, only the households with the lowest incomes benefit from increased transfers. Households of the latter type, however, benefit at any of the first twenty income percentiles. Moreover, the state options in the TANF program result in large disposable income discrepancies for identical earned incomes; as shown in 4b, a Jones household earning about $7,500 in California and Texas is left with a disposable income of about $18,000 and $12,700, respectively.

Our results for the single filer indicate that this prototype household receives small amounts of transfers only at the lowest incomes. Thus, in combination with the unavailable income support from tax programs mentioned above, this leaves the single filer with only limited access to the safety net; even in states commonly considered generous in social insurance programs, for example California and New York, this household remains a net tax payer even at earned incomes of about $9,000.[22]

Finally, including Medicaid and CHIP exacerbates the cross-state heterogeneity of marginal tax rates reported for the Miller and Jones family type as shown by figures 38 to 40 in appendix H.1. However, the single filer is not eligible to participate in these programs in any state and so the findings for this prototype household are unaffected. In summary, our measures of the lowest incomes in each state and the imputation model we constructed using various tax and transfer calculators provide us with a suitable representation of marginal tax rate variation within and across states for low-income households with different demographic characteristics.

[22]Indeed, this relative lack of income support for childless households has been noted previously in studies on the US safety net and is a pivotal element in the debate on Universal Basic Income (UBI). See, for example, Hoynes and Rothstein (2019).

4.2 Insurance against Earnings Loss

In this section, we use our model to estimate the share of earning shocks absorbed by changes in federal and state taxes and transfers. In our baseline analysis, we consider a shock size of 50%. As we explain in appendix B, this magnitude is a good representation of earning shocks experienced by American low-income households. We compute our χ measure of insurance by imputing taxes and transfers at the pre-shock level of earned income. Next, we reduce this income by 50%, repeat the imputation and study the changes in taxes and transfers relative to the shock size.

This approach assumes a shock duration of twelve months. So one can think of this exercise as comparing the disposable incomes of the same prototype households in two consecutive years where earned income in year $t+1$ is 50% lower than in year t but all else is kept fixed. An alternative interpretation is to think of two identical families – one experiencing the shock, the other does not. To explore insurance against shocks of different durations, we reduce it to one month and report results in appendix H.2.

It can be argued that the insurance measures we compute reflect lower bounds on the pass-through of shocks to disposable income; they capture public sources of insurance (taxes and transfers) and abstract from private channels of insurance. However, for hand-to-mouth households, who are our population of interest, self-insurance from (precautionary) savings is of second order importance. Thus, our findings can be considered good approximations of the actual insurance available to working poor households.

Our analysis focuses on the years 2000 to 2007. This period is well past the major welfare reform of 1996 and pre-dates the effect of the Great Recession on the US social safety net. Moreover, it is unaffected by large federal or state reforms such as the Affordable Care Act (ACA) which effected large Medicaid expansions. Finally, to arrive at results which capture fundamental and long-term state differences, we estimate our measure of tax progressivity for each year and state and then average it per state.

4.2.1 Federal Perspective

As a point of departure, we start from nominal incomes equal to the Federal Poverty Limit (FPL) for each prototype household and year.[23] These nominal income levels are natural benchmarks for federal policies as they constitute nation-wide yardsticks to identify households in or at risk of poverty. In fact, many safety net transfer programs use them as parameters to determine eligibility and generosity. Thus, this analysis captures the 'federal perspective' on the provision of income insurance.

Another reason why we start our investigation from these income levels is that the federal system treats households at identical nominal income levels alike in terms of taxes and transfers, irrespective of their state of residence. Thus, measuring the insurance against an earnings

[23] For the 48 contiguous states and DC in 2000 (2007) these amounts were $17,050 ($20,650) for the Miller family, $14,150 ($17,170) for the Jones family and $8,350 ($10,210) for the single filer. Note that Alaska and Hawaii have slightly higher FPL levels.

shock which reduces a uniform fraction of this starting point allows a clear identification of differences driven by state tax and transfer policies as it mutes differences in state income distributions. We present two sets of results as we first compute our measure of insurance using nominal (US Dollar) values. In a second step, we illustrate cross-state differences using real values.

Nominal Values Figure 6 shows the sources of insurance available to the Miller family and their respective magnitudes. As the figure illustrates, averaged across all years, our estimate of total insurance ranges from about 80% to 30%. Put differently, in some states (Alaska, California, Hawaii, Massachusetts, etc.) about 20% of the shock are passed to disposable income while this value is about 70% in most others.

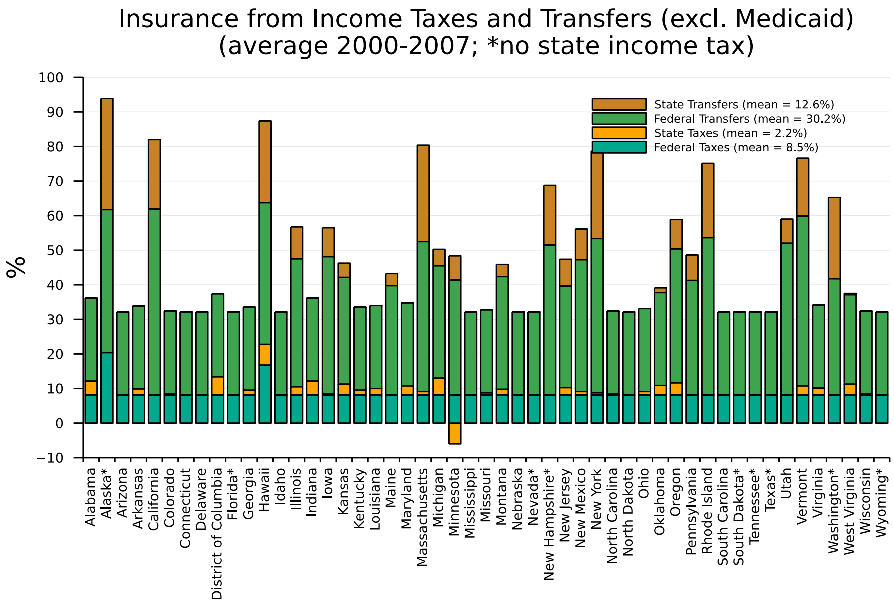


Figure 6: *Miller Family - Decomposition of* χ

As the starting earnings level and the shock size are the same in all states, insurance from federal taxes is identical (except for Alaska and Hawaii which have different FPLs) and estimated at 8.5% on average between 2000 and 2007. This estimate can be further decomposed into several elements of the federal income tax system. For ease of exposition, consider the year 2005. First, taxable income of the Miller family is zero before and after the shock.[24] As a result, the insurance from changes in regular federal income taxes is zero. Second, as the FPL is far below the assessment limit of the Social Security's Old-Age, Survivors, and Disability Insurance (OASDI) program, federal payroll (FICA) taxes are linear in earned income, and constitute about 15% of earned income before and after the shock. Thus, they reduce the shock by 15%.

Third, both before and after the shock, the family qualifies for the federal Earned Income Tax Credit (EITC). Appendix C illustrates the parameters of this program and its terminology. Before the shock, the earned income places the family into the phase-out range of this program.

[24]This is different for Alaska and Hawaii due to the higher FPL. In those states, the Miller family has positive taxable incomes and minor income tax liabilities (before applying credits) at the pre-shock level of earnings.

The after shock income, however, is so low that it falls into the phase-in range. As a result, the increase in the EITC amount is very small ($3,772 before the shock, $3,870 after) which limits its capacity to provide insurance. Moreover, before the shock, the family's Child Tax Credit (CTC) was greater than the amount of income tax owed and so it was eligible for the Additional Child Tax Credit (ACTC) and received $1,253 from this program. Yet, the family's post-shock earned income is below the ACTC refundability threshold. As a result, the Miller family loses eligibility.[25] Thus, as the net support provided by refundable tax credits is lower after the shock than before, this element of the federal income tax code makes a negative contribution to income insurance which results in total insurance from federal income taxes equal to 8.5%.

State income taxes also provide some insurance albeit to a much smaller extent. For example, for Alabama, DC, Hawaii, Indiana and Michigan, our model computes a χ^{s}_{taxes} of about 0.03 and 0.04, averaged across all years between 2000 and 2007. In other words, changes in state income taxes absorb about 3 to 4% of the earnings shock. The average across all states which provide some insurance is 2.2%. However, in most states, this source of insurance is small or zero (in all states which do not have income taxes). Finally, in Minnesota, the Miller family is no longer eligible to the "Working Family Tax Credit" which results in a negative contribution to income insurance in this state.

Lastly, figure 6 shows large cross-state discrepancies in insurance capacity of state and federal transfers. Moreover, on average, they provide more insurance than income taxes. Yet, in some states, only federal transfers are estimated to make a positive contribution. The reason is that, at the post-shock level of earned income, the family qualifies for more generous SNAP benefits in *all* states. Thus, it always enjoys larger SNAP payments after the shock. However, it does not qualify (for more generous) TANF benefits in some states. This is because state governments determine TANF eligibility and generosity. But, as the benefits of this transfer program are partly financed by federal block grants, it mechanically receives more insurance from federal transfers in states where it does qualify. Hence, the large discrepancy in total transfer insurance is driven by the state options of TANF.[26]

As figures 7 and 8 show, the insurance value of state income taxes for the Jones and Single Filer household types is very similar to the case of the Miller family; on average, they absorb about 2.2% (2.4%) of the earnings shock in some states but their insurance contribution is zero in most states. The role of federal income taxes, however, is strikingly different; both prototype households have zero federal taxable income before and after the shock. However, the single filer enjoys a large insurance effect as changes in federal income taxes absorb about 20% of the shock. The reason is that the EITC is more generous after than before the shock. As the Millers, the single filer's earned income moves from the phase-out into the phase-in range and

[25] This threshold was $10,000 in 2005 as documented by Crandall-Hollick (2018). Indeed, the lack of support from the ACTC for families with very low incomes has been pointed out previously, for instance by Burman and Wheaton (2005).

[26] As shown in figure 41 of appendix H.1, the difference in insurance provided by transfers increases even further when we include Medicaid. As TANF, this program has state options regarding eligibility which differ strikingly across states. In some states, the Miller family qualifies for neither of these two transfer programs at the post shock level of earnings. In others, it qualifies for both. As a result, state and federal transfer policies differ in their capacity to stabilize household disposable income.

the EITC increases from \$168 to \$366. The Jones family, on the other hand, receives a lower EITC (\$4,037 versus \$3,218) and, as the Millers, falls below the ACTC refundability threshold at the post-shock income so its ACTC equals zero and was \$764 before the shock. Thus, except in Alaska and Hawaii, this prototype household experiences a negative insurance effect from federal income taxes.

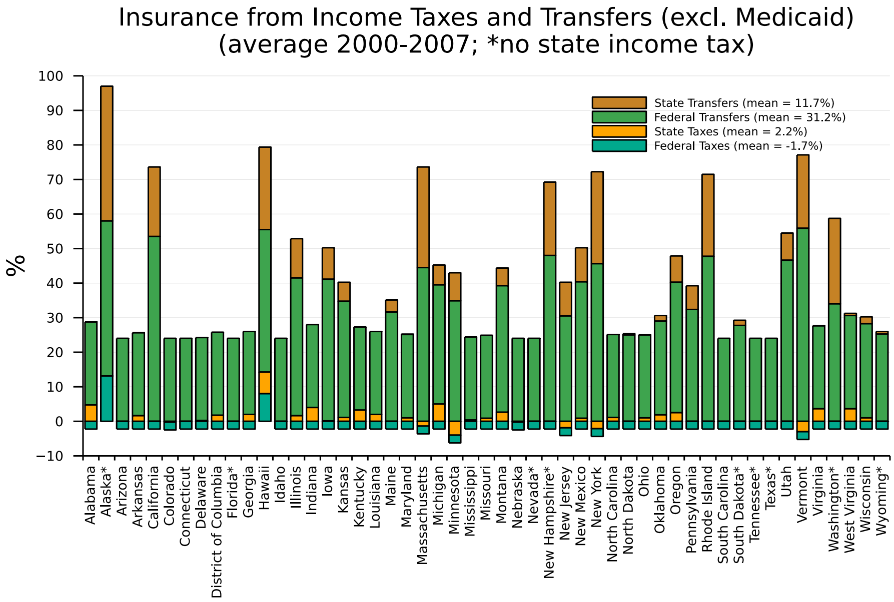


Figure 7: *Jones Family - Decomposition of* χ

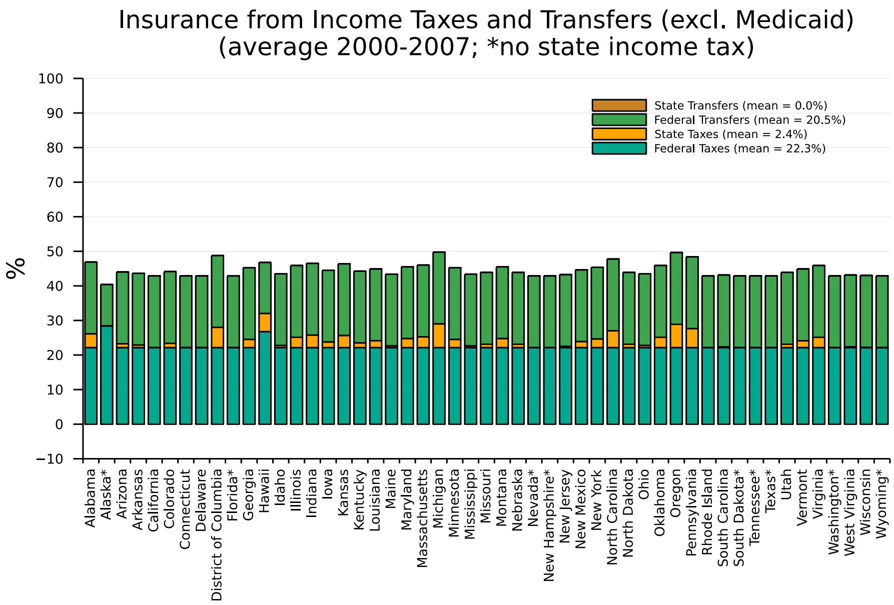


Figure 8: *Single Filer - Decomposition of* χ

Regarding transfers, figures 7 and 8 illustrate that for the Jones family, the magnitude of insurance provided by transfers is similar to the case of the Miller family; it is substantial in states with generous TANF implementations. In those without, increases in federal transfers (SNAP) absorb about 25% of the earnings shock. The Single Filer, on the other hand, never receives any insurance from state transfers as this prototype household does not qualify for TANF in any state. Therefore, the contribution of state transfers are estimated as zero in figure 8 and this household receives insurance only from federal (SNAP) transfers.

Real Values In the previous paragraph, we studied the response of taxes and transfers in each state to a 50% loss of earned income. As pre-shock earnings, we chose the FPL. Thus, we assumed a common nominal starting point and the same shock size in nominal terms (with the exception of Alaska and Hawaii). Given the considerable cross-state price differences in monthly subsistence expenditures we document in sections A and F of the appendix, this analysis assumes that each household loses the same amount of nominal income, even though the shock size differs across states in *real* terms. To address this dimension of state heterogeneity, we now divide nominal US Dollar amounts by state and household specific subsistence expenditure prices so we can study the differences in public insurance from a *real* perspective.

Specifically, we express the shock in multiples of monthly subsistence expenditures. For each prototype household, these 'expenditures baskets' represent the number of months each family can afford to pay for food and housing. For the Miller Family, figure 9 shows that, measured in months of subsistence spending, the shock studied in the previous paragraph represents between 5.5 (in expensive states) and 11 (in cheap states) months of spending. For the Jones Family and the Single Filer, these amounts are slightly higher and lower, respectively, as illustrated in figures 10 and 11. (For ease of exposition, the figures plot the joint insurance effect of income taxes and transfers for each level of government.)

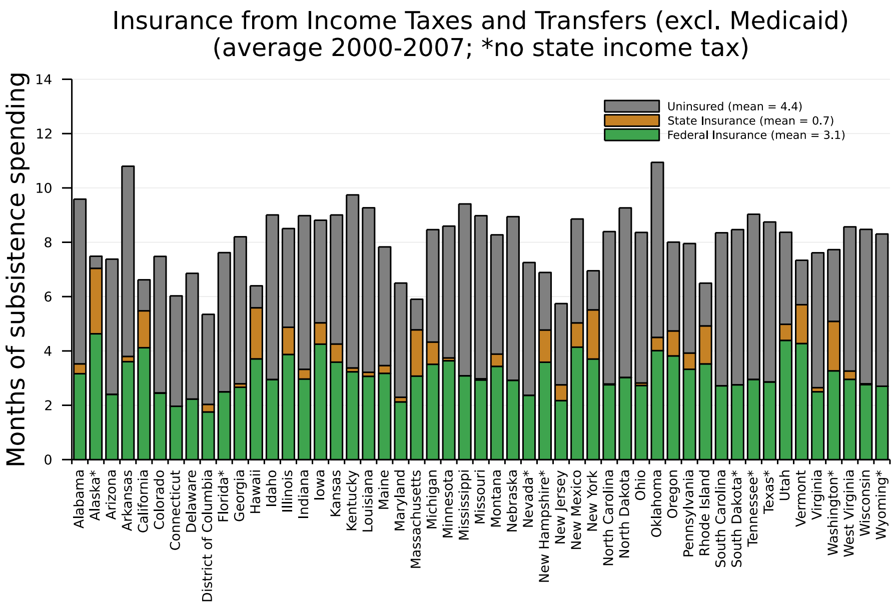


Figure 9: *Miller Family - Shock and Insurance in real terms*

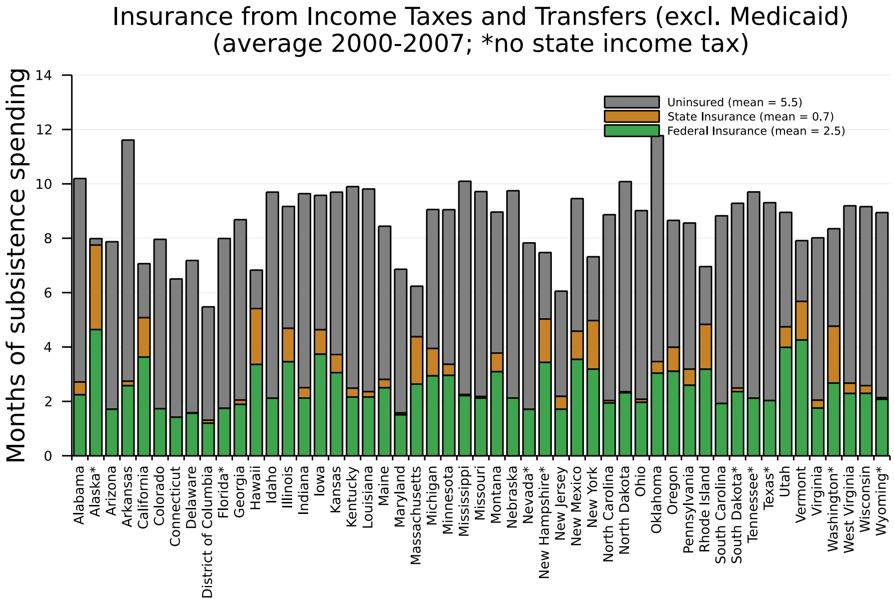


Figure 10: *Jones Family - Shock and Insurance in real terms*

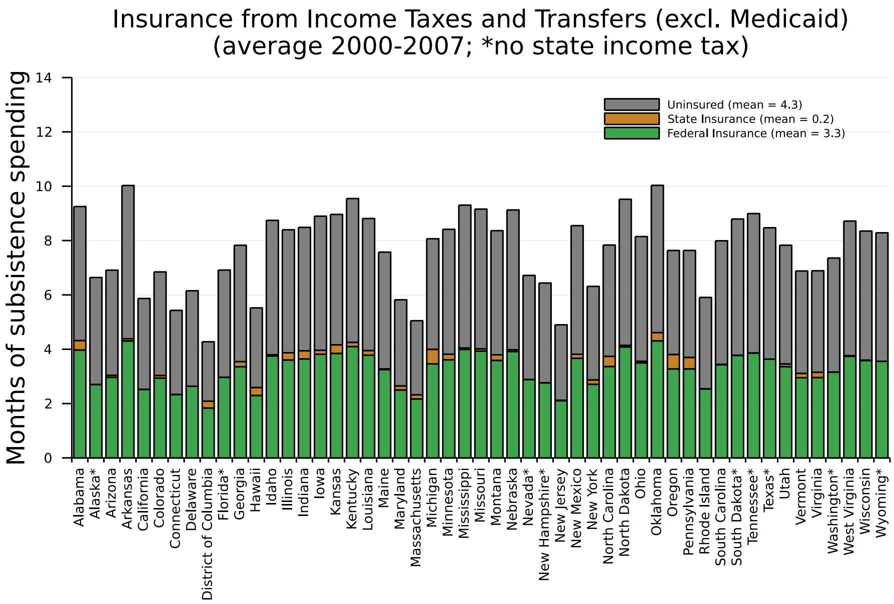


Figure 11: *Single Filer - Shock and Insurance in real terms*

For the Miller Family, the uninsured number of the lost baskets varies between 1.5 and 7. For the other prototype households, the pass-through ranges from 0.25 to 8.5 (for the Jones family) and from 2 to 6 (for the Single Filer). These numbers represent the equivalents of monthly subsistence spending which are uninsured by taxes and transfers, i.e. the families' disposable incomes are lowered accordingly. By construction, as a share of the shock size, the real amount of insurance is inversely related to the one computed in nominal terms. For example, for the Miller family, our estimate of total nominal income insurance in Alabama is $\chi^{total}_{Alabama} = 0.37$. In real terms, it is $6/9.5 = 0.63 = 1 - \chi^{total}_{Alabama}$.

However, compared to the nominal insurance values, the real perspective shows that federal insurance is no longer uniform. This is due to cross-state price differences; in expensive states, the nominally uniform federal taxes and transfers absorb about two months of subsistence spending. In cheap states, this number is closer to four.[27]

The same discrepancy applies to state policies. In nominal terms, some states appear to provide much more insurance than others. Yet, when we take into account state specific price levels, these differences are much more nuanced. Moreover, state choices do not appear to account for the interaction of uniform federal policies and state specific price levels; in other words, states with high subsistence cost do not compensate for the low real value of federal policies by choosing particularly generous taxes and transfers. Hence, as in nominal terms, state differences against earning shocks prevail also in real terms.

4.2.2 State Perspective

In this section, we investigate federal and state insurance against shocks to nominal earnings which differ by state, year and prototype household. Specifically, for each state, year and family, we compute the change in taxes and transfers for a loss of 50% shock for each percentile of the 20 lowest incomes and impute the changes in federal and state taxes and transfers.[28] This approach allows us to capture differences in nominal state income distributions which have implications for the insurance effect of federal policies. Moreover, it considers the 'state perspective' on income distributions; depending on average state incomes, different income levels are associated with households being in or at risk of poverty. For those reasons, we consider this analysis our baseline case.

In order to wash out year effects and to arrive at persistent estimates of state policy choices, we average over all 20 income percentiles and years from 2000 to 2007. We do this separately for federal and state income taxes as well as transfers. Finally, we also account for price differences and we report results of including the transfer program Medicaid in appendix H.1.

Nominal Values As illustrated by panels (a) of figures 12 to 14, our model now computes estimates of the nominal insurance provided by federal taxes which are no longer uniform across states. The reason are the state-specific nominal differences in earned incomes. Hence, the insurance effect of changes in federal income taxes and tax credits vary across states. For the Miller prototype household, their contribution to income insurance is much larger than in the case of the FPL starting point. This discrepancy is driven by the fact that the mean of the 20 first income percentiles is generally larger than the FPL income level. Hence, the family receives more generous amounts of tax credits after experiencing a shock to earnings and so the insurance effect of federal taxes is larger than in the case of the FPL starting point.

The same is true for the Single Filer; the insurance effect of federal taxes is (slightly) larger than for the uniform earnings level. For the Jones family type, however, the opposite applies; the

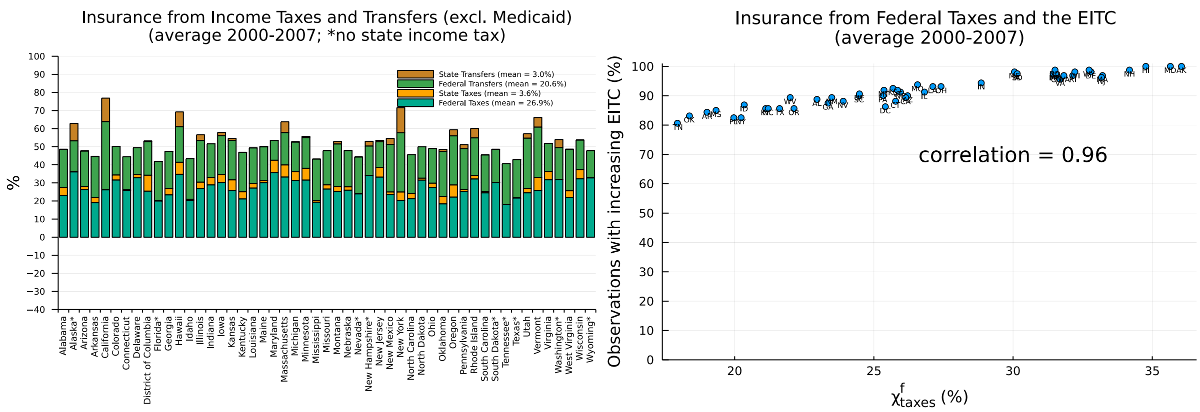
[27] Figure 35 in appendix F shows state specific prices of the subsistence basked for each prototype household, averaged over the years 2000 to 2007.

[28] We explain in section G of the appendix how we construct these income percentiles.

mean of its 20 first income percentiles is (much) smaller than the FPL income level. Thus, at the after-shock level of earnings, it is generally in the phase-in range of the EITC and below the refundability threshold of the ACTC. Therefore, the insurance effect of federal taxes is estimated to be negative in all states.

Given the importance of the EITC for the efficacy of the federal income tax system, panels (b) of figures 12 to 14 correlate the insurance effect of federal taxes, χ^{f}_{taxes}, with the fraction of the 20 income levels which experience a change in their EITC benefits. As these scatterplots illustrate, changes in this program alone explain the majority of federal insurance. The remainder is due to changes in regular federal income tax liabilities. However, these matter only in states with relatively higher nominal incomes (such as Maryland and Connecticut).

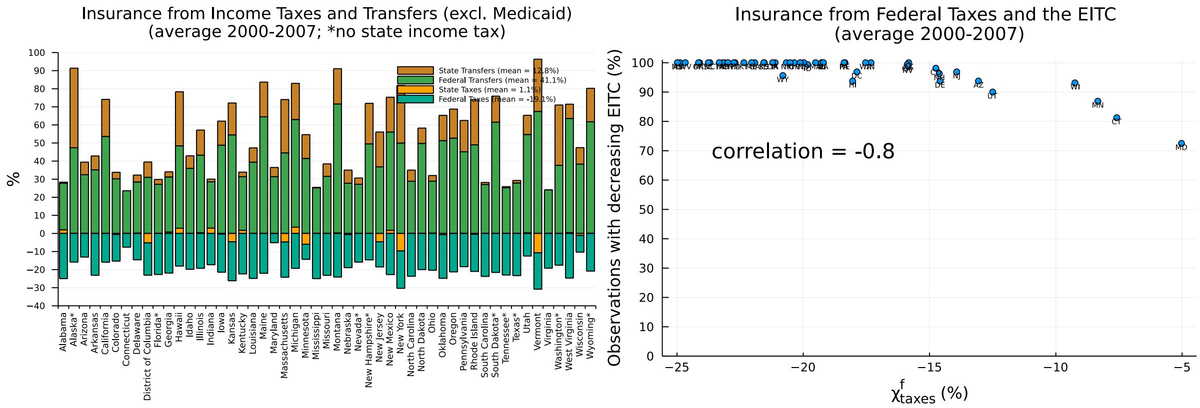
For the Miller and Single Filer prototype households, changes in state income taxes absorb about 3% the shocks to earnings. Now, every state with an income tax provides some positive insurance, reflecting that state policy makers target their tax systems to respond to income levels associated with poverty in their jurisdictions. In fact, in some states, their insurance value is estimated at about 8% which is about a quarter of insurance provided from federal sources. However, as shown in figure 13a, state income taxes make negative contributions to insurance for the Jones family in select states. These are, for example, Kansas, Massachusetts, New York and Vermont which have refundable earned income or child tax credits.[29] As for federal tax credits, at the after-shock level of earned income, the Jones family no longer qualifies for them.



(a) Federal versus state decomposition (b) EITC and insurance from federal taxes

Figure 12: *Miller Family*

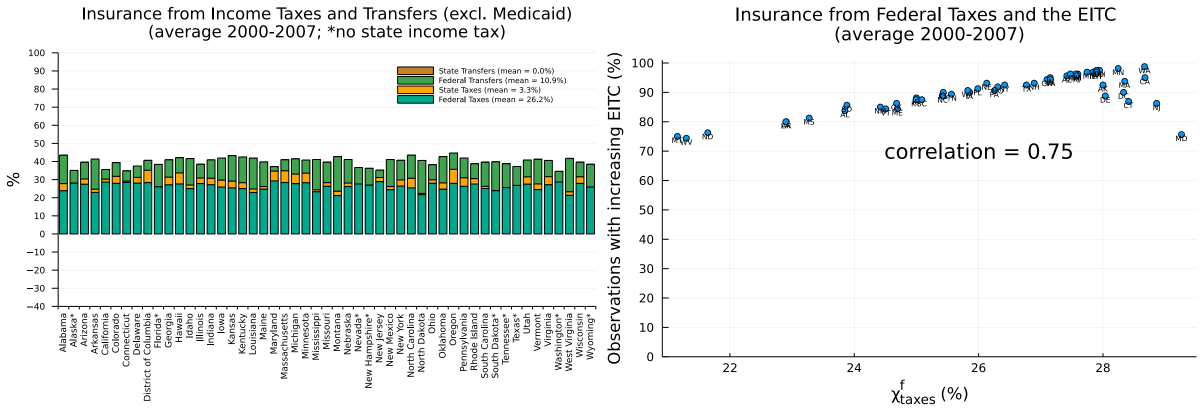
[29]See table 7 in appendix C for a summary.



(a) Federal versus state decomposition

(b) EITC and insurance from federal taxes

Figure 13: *Jones Family*



(a) Federal versus state decomposition

(b) EITC and insurance from federal taxes

Figure 14: *Single Filer*

For the Miller and Single Filer prototype households, state and federal transfers play a much smaller role in absorbing the earning shocks than in the case of the FPL starting point. Again, this is because the mean of the 20 first income percentiles is generally larger than the FPL income level. Importantly, the single filer still does not qualify for any state transfers as TANF eligibility requires the presence of children – independent of any income level. The Jones family, on the other hand, receives higher transfers at the after-shock earnings level than the pre-shock level in almost every state. However, there are large cross-state differences in transfer generosity; in some states, changes in state transfers alone absorb about 40% of the shock while their insurance effect is zero in others. Yet, in all states, changes in federal transfers make a positive contribution in insurance for this household.

Compared to the case of the uniform level of earned income presented in section 4.2.1, we find a higher average amount of income insurance for the Miller family and less cross-state variation. This moderation is driven by a decrease in the insurance provided by transfers with state options. The reverse is true for the Jones family; in most states, transfers now provide much more income insurance which drives up average insurance but large cross-state discrepancies remain. For the Single Filer, there are only minor differences in total insurance between the FPL and baseline results.

Real Values As for the case of the FPL before-shock earnings, we again adjust the nominal results presented in the previous paragraph by state and household specific prices to study the *real* generosity of state tax and transfer programs. The results are presented in figures 15 to 17.

As before, the purchasing power adjustment results in variation of federal insurance for all household prototypes. For the Miller family, it varies between 4 and 6 months. Thus, it is generally larger than in the case of FPL starting earnings. However, the insurance contributions of state taxes and transfers are (much) smaller; they never absorb more than one month of spending. Also, they do not differ as much across states. Together, state and federal policies absorb about 50% of the real value of the earnings shock across states. We find similar results for the Single Filer. For this prototype household, changes in transfers and tax credits are slightly less generous. However, as the subsistence spending prices for this household are much smaller than for the Miller family, this discrepancy only results in marginally smaller insurance.

For the Jones family, due to its relatively lower income, the shock expressed in months of subsistence spending is much smaller than for the other prototype households. However, in real terms. it enjoys the least amount of insurance of all three household types. The reason are the negative insurance contributions of federal and state income taxes. As shown in figure 13a, they offset the positive contributions of transfers in some states. Hence, in these states (for example Alabama, Florida, Georgia and several others), all of the shock is passed to disposable income as net insurance is zero. As figure 16 illustrates, this translates into a required reduction of subsistence spending of up to six months.

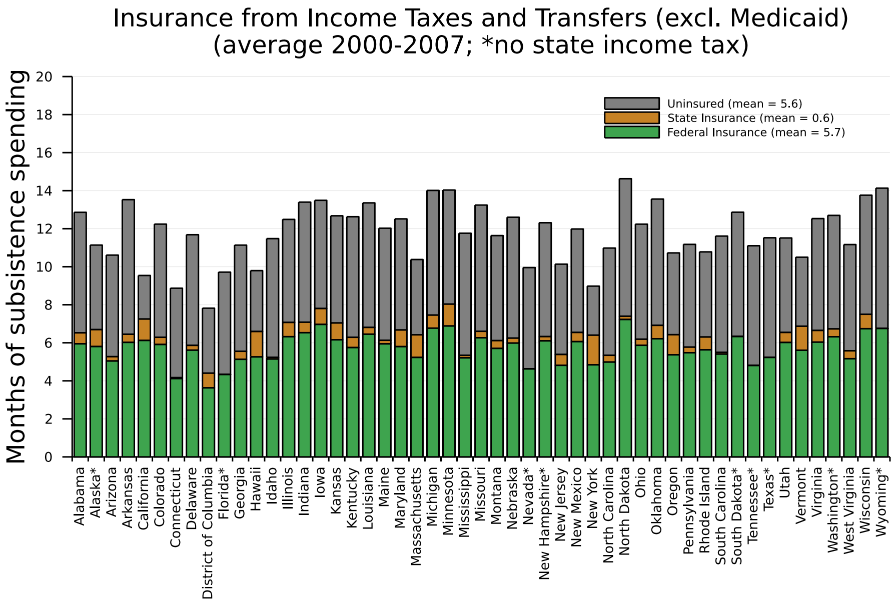


Figure 15: *Miller Family - Shock and insurance in real terms*

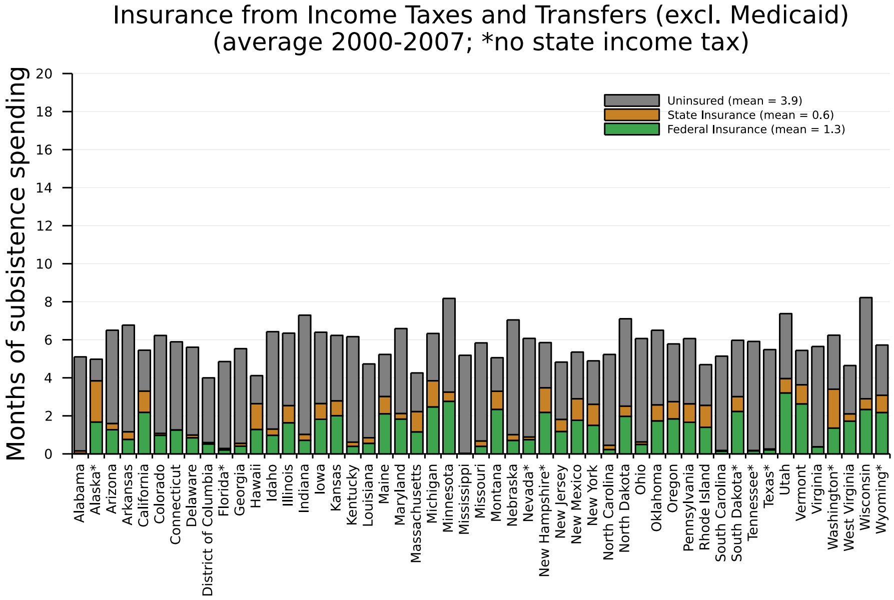


Figure 16: *Jones Family - Shock and insurance in real terms*

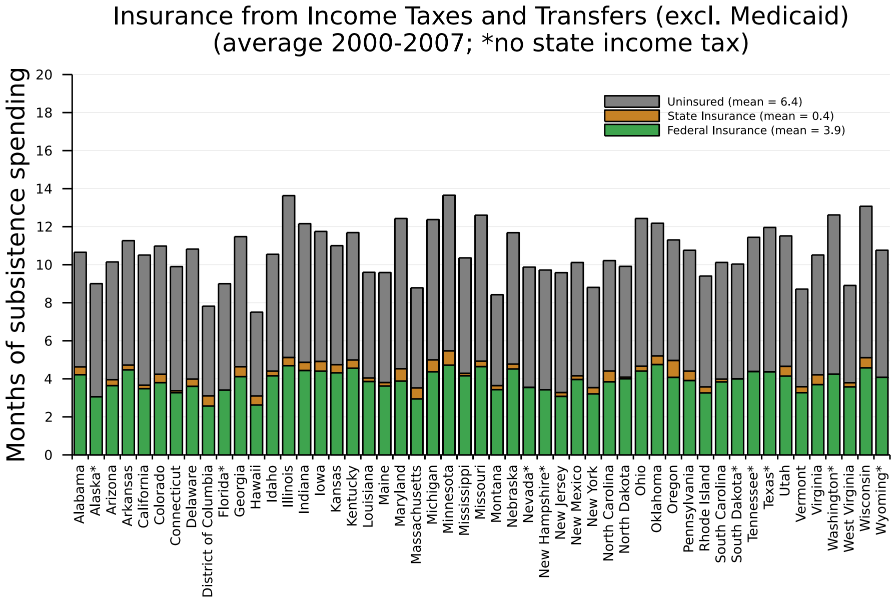


Figure 17: *Single Filer - Shock and insurance in real terms*

Comparison of Findings To assess the robustness of the variation in income insurance across states and prototype households, we now investigate the correlations between our different insurance metrics for the baseline results presented in the preceding section 4.2.2.

For this analysis, we compute the correlation coefficients between the nominal and real insurance measures for each household type; we then compute the pairwise correlations between each household type, for each of the insurances measures. For the former analysis, the resulting coefficients are presented in table 3. They show that regardless of whether we include Medicaid and CHIP transfers in the computation, the correlation between nominal and real measures is very high. Thus, while the magnitudes of our measures are affected by the inclusion of this transfer program, our real and nominal baseline results point to meaningful cross-state differences in the impact of tax and transfer policies on absorbing shocks to earnings.

	Miller	**Jones**	**Single Filer**
excl. Medicaid	0.90	0.92	0.89
incl. Medicaid	0.89	0.81	0.89

Table 3: *Pearson correlation between nominal and real measures (baseline results)*

Measure	**Miller, Jones**	**Miller, Single Filer**	**Jones, Single Filer**
excl. Medicaid			
Nominal (χ)	0.39	0.49	0.02
Real (baskets)	0.34	0.50	0.03
incl. Medicaid			
Nominal (χ)	0.36	0.30	-0.00
Real (baskets)	0.34	0.29	0.01

Table 4: *Pearson correlation between prototype filers (baseline results)*

The results of correlating our insurance metrics across prototype households are presented in table 4. They indicate that our estimates are highly correlated for the Miller and Jones households and again for the Miller and Single Filer types. However, they are much less correlated between the Jones and Single Filer prototype households. The reason is twofold; first, insurance provided by federal and state income taxes is very similar for the Miller and Single Filer type. However, as discussed above, the Jones household generally receives little or negative insurance from this source. Second, the role of insurance from transfers is large for households with children such as the Miller and Jones prototypes. However, as a childless household, transfers are less relevant for the Single Filer. Both of these observations explain the correlations illustrated in table 4.

4.3 Insurance against Job Loss

In this section, we study insurance against the risk of unemployment episodes, during which the household's earnings are reduced to zero. Unemployment insurance (UI) is administered by state governments while the federal government's only roles are to act as custodian for the states' UI trust funds and to provide extended ('emergency') benefits in exceptional circumstances, such as a severe nationwide recession. Accordingly, states have wide discretion over program parameters such as weekly benefits, waiting weeks and dependent allowances. This program therefore reflects another dimension of state differences in income stabilization. In

Appendix E we provide details on how we account for these state choices to impute unemployment benefits (UB).

To choose a shock size for this exercise, we obtain data on the seasonally adjusted median weeks of unemployment for years 2000 to 2007 from the Bureau of Labor Statistics (BLS).[30] Our investigation assumes that each prototype family experiences job loss lasting for this number of weeks within a given calendar year. During this unemployment spell, we replace the earned income with the amount provided by the state specific unemployment insurance system. We also compute the insurance provided by any changes in taxes and transfers related to the temporary loss of earned income.

Given the state policy options, we choose the same nominal earned incomes as in our baseline analysis, i.e. the first twenty percentiles of each state's income distribution (as opposed to the FPL). Moreover, to account for price differences, we compute the generosity of unemployment benefits relative to monthly expenditures and present results in real terms. They are shown in figures 18 to 20.

We first highlight that there are noticeable differences in the size of the shock between household types. Recall that the living cost measure is specific to the type of household as well as the state. While for the Miller Family and the Single Filer, the unemployment shock reduces earnings by between 2.5 and 4.5 months of subsistence spending (depending on the state), for the Jones family it equates to between 1.5 and 2.8 months of spending. The explanation for this is twofold. The shock to the Miller household's income is larger because this household has two working adults and we assume that the unemployment shock affects both of their incomes. For the Single Filer, the shock is larger *in real terms* because the living cost which is applied to the shock is much lower, since the Single Filer's household consists of one person while the Jones household has three.

For all three prototype families, UI makes the largest contribution to insuring the unemployment shock, followed by federal taxes and transfers. For the Miller Family, UI accounts for between 1 and 2.4 subsistence baskets, depending on the state of residence. We see that in all states (with the possible exception of New Mexico), some portion of the unemployment shock is left uninsured for the Miller family, meaning that the household would need to reduce its consumption or rely on private channels of insurance. However, the vast majority of the unemployment shock is absorbed in all states, suggesting that state policies are well targeted towards this kind of risk for the Miller family. For the single filer family, the insurance against an unemployment spell is slightly less generous, but this is mostly explained by a smaller response of federal taxes and transfers. Unemployment insurance makes a larger contribution, absorbing between 1 and 2.1 months of subsistence spending.

For the single parent household, there is much more variation across states in the insurance against unemployment risk. While in the more generous states (such as Alaska, New Hamp-

[30]The number of weeks is provided by month and we take annual averages to obtain a measure for each year. Values range from six weeks in 2000 to ten weeks in 2003 and 2004. Note that no state unemployment system has a maximum duration below this number. Thus, differences in our estimated measure of insurance are not driven by this aspect.

shire, or New Mexico), the combination of state and federal policies absorbs the entire loss of earnings, in the less generous states (such as South Carolina, Tennessee and Texas), the total policy response absorbs less than half of the shock to earnings from the unemployment spell. The variation across states is again driven to a large extent by federal taxes and transfers, as in some states the household is already close to exhausting is eligibility for federal transfers. However, we also see that in the states that provide more insurance against the unemployment shock, state level taxes and transfers make an important contribution.

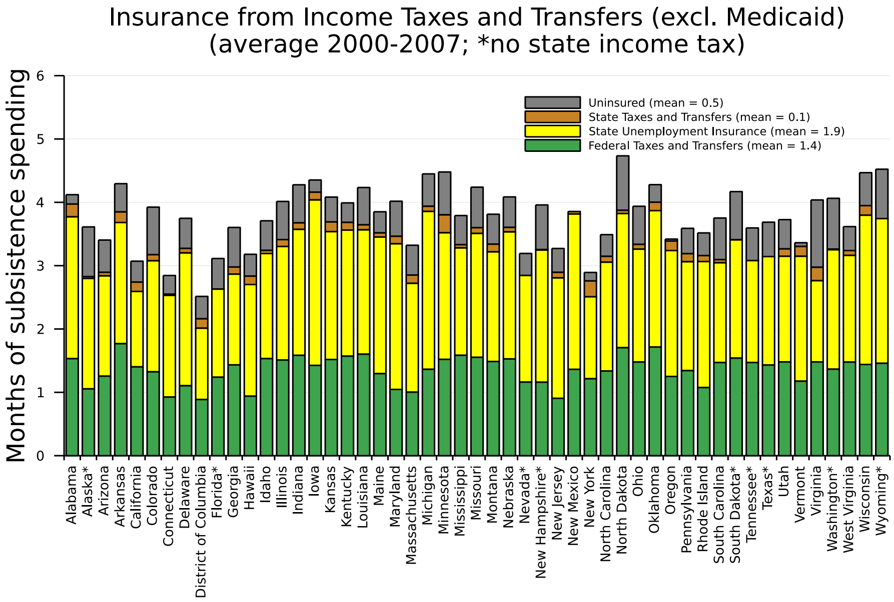


Figure 18: *Miller Family - Unemployment insurance in real terms*

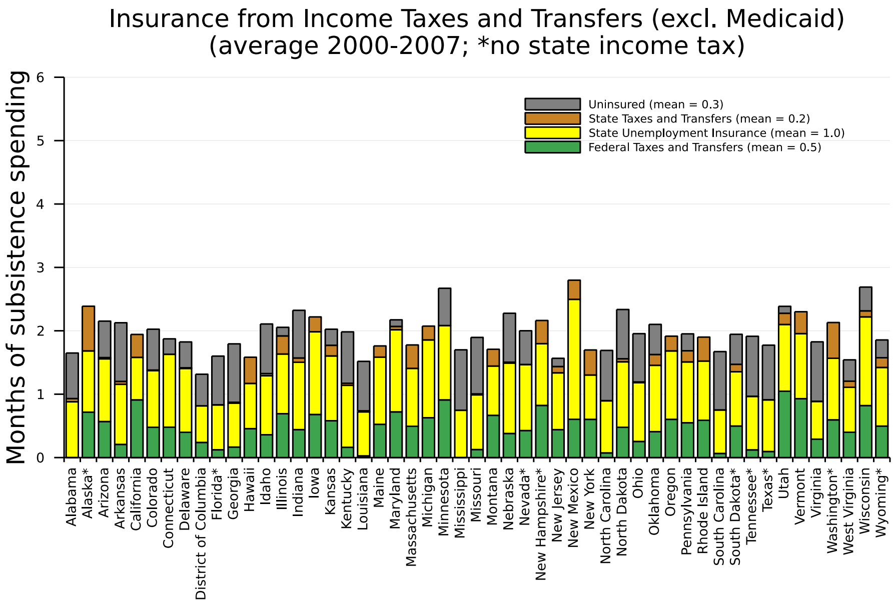


Figure 19: *Jones Family - Unemployment insurance in real terms*

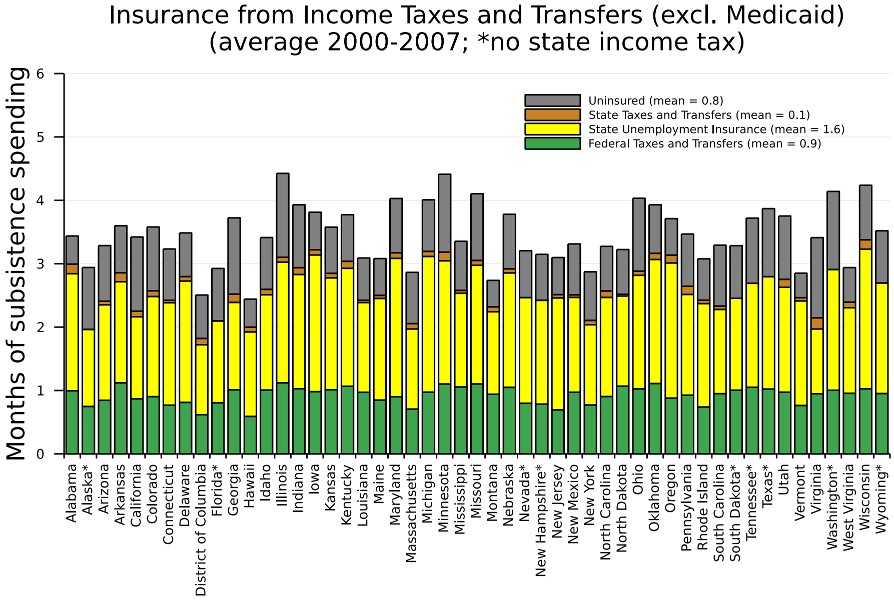


Figure 20: *Single Filer - Unemployment insurance in real terms*

5 Income Insurance and State Characteristics

The results so far identify fairly robust geographical variation in the level of earnings support provided to low income households in different states. Figures 21 to 23 show the geographic distribution of our measure of income insurance for each of the three prototype households for the baseline case, i.e. experiencing a 50% shock from the first twenty income percentiles and adjusting by the prices of monthly subsistence spending. A natural question to ask is what state characteristics can help to explain this variation. Therefore, in this section, we perform a regression analysis to identify state-specific factors which may be associated with insurance provision.

Specifically, we are interested in how much of the cross-state variation can be explained by state characteristics such as the share of the population living in urbanized areas and the share of black residents, the political leaning of voters and the level as well as dispersion of mean household earnings. In addition, we also control for the state price measures we constructed for our three prototype filers and a basic feature of the state tax system, namely whether it taxes income. Appendix I.1 summarizes the data we use to construct these covariates.

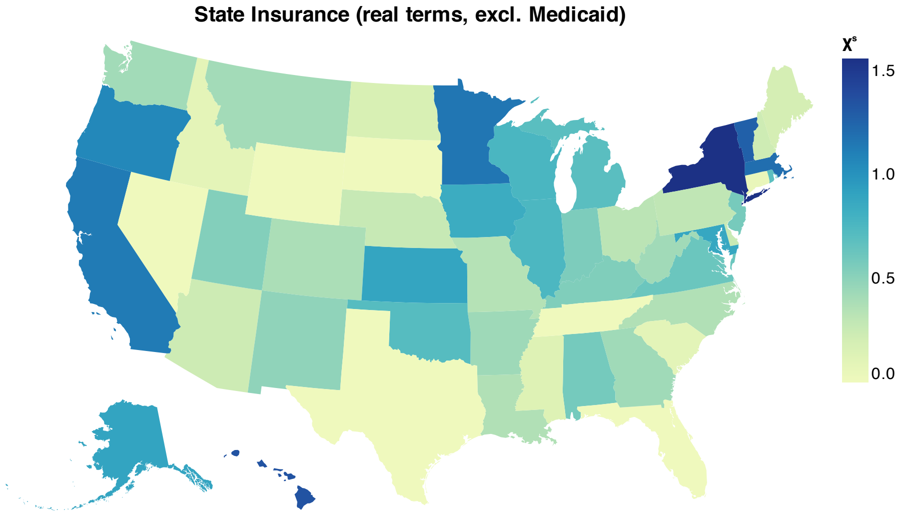


Figure 21: *Miller Family - Geographic distribution of insurance (real terms)*

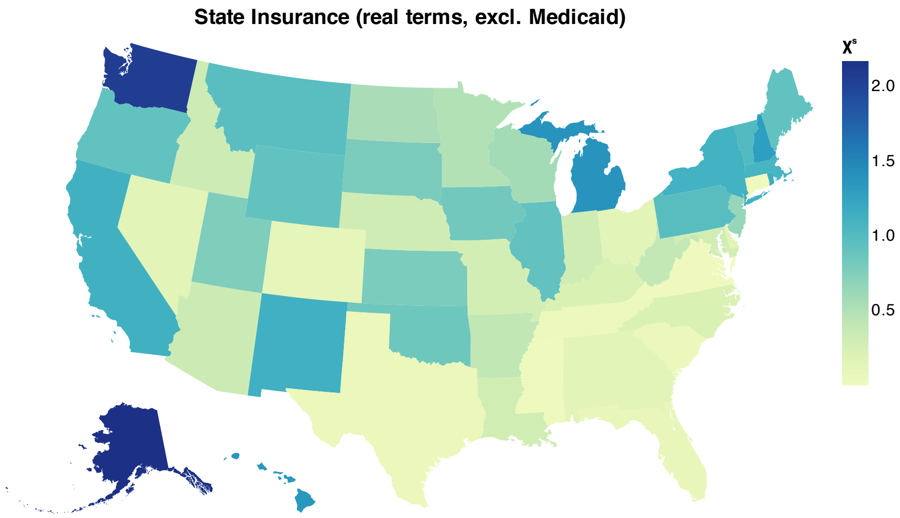


Figure 22: *Jones Family - Geographic distribution of insurance (real terms)*

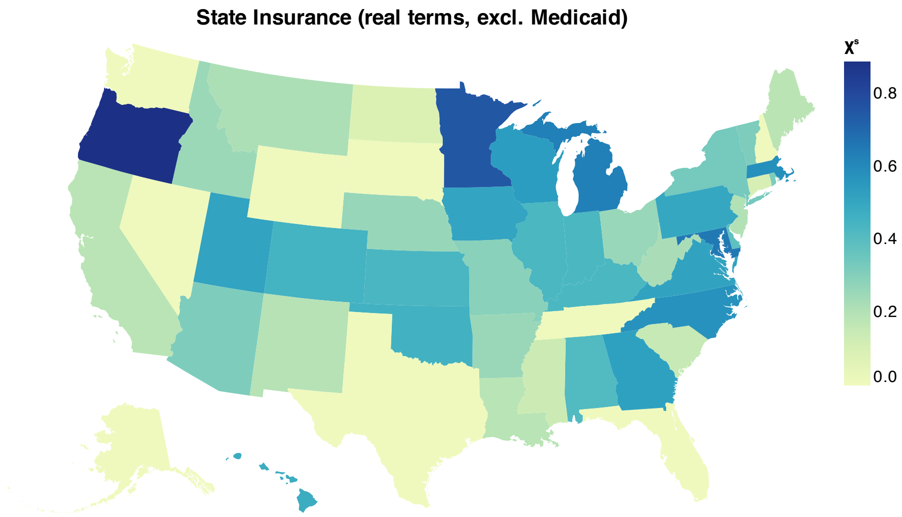


Figure 23: *Single Filer - Geographic distribution of insurance (real terms)*

As table 5 illustrates for the Miller family prototype household, states with higher price levels, more Democrat leaning voters and with a tax on income provide more insurance. As higher state price levels translate to more insurance, states appear to target their policies to some extent to reflect the cost of living. As expected, the price effect drops to zero when we investigate variation in the real measure for insurance. However, the coefficient estimates for the political tilt and the role of the income tax remain large and significant. For example, the difference between taxing income or not results in an insurance value equal to about one third of monthly subsistence spending. When we include the Medicaid program in our estimation, all state characteristics except the share of black residents become insignificant. The estimate of this covariate indicates that states with higher shares of black residents provide less insurance, both in nominal and in real terms.

For the Jones family, this observation applies to all insurance measures. In addition to the price level and political indicator, table 6 shows a negative and significant coefficient estimate on the share of the black population. This finding is consistent with earlier studies which found that discrimination against black people is a visceral feature of the US social safety net; southern US states systematically choose more restrictive state options in welfare programs.[31] Even though the magnitude is smaller than the estimates for the role the price level, the political color and mean income, it is negative and significant for all measures of earnings insurance. However, for this household type, the presence of a state income tax seems to be of second order importance compared to the Miller family. This finding is driven by the supreme role of transfers for the household head family type. As its income is too low to qualify for substantial state earned income and child tax credits, the bulk of insurance is provided from transfer programs.

Finally, we report the results of the analogous regression analysis for the Single Filer household in appendix I.2. For this type, the only significant covariate is the presence of a state income tax

[31] In the words of Moehling (2007), p. 27: "Although welfare policy may not have been responsive to the needs of white or black families, at many junctures it was set so as to discriminate against blacks."

while none of the other state level characteristics are found to explain the cross-state variation of our insurance measure.

	Nominal (χ)	Real (baskets)	Nominal (incl. Medicaid)	Real (incl. Medicaid)
	(1)	(2)	(3)	(4)
Constant	-14.335	-0.333	-23.314	-0.589
	(13.852)	(1.358)	(31.624)	(3.142)
Price Level	0.009**	0.000	0.020*	0.001
	(0.004)	(0.000)	(0.010)	(0.001)
Democrat (0/1)	2.984**	0.293**	4.756	0.421
	(1.332)	(0.131)	(3.040)	(0.302)
Has Income Tax	3.152**	0.372***	2.091	0.204
	(1.318)	(0.129)	(3.009)	(0.299)
Gini Coefficient	20.175	0.216	35.314	0.509
	(32.063)	(3.143)	(73.196)	(7.273)
Mean Income	-0.076	-0.002	-0.143	-0.008
	(0.104)	(0.010)	(0.236)	(0.023)
Share Urban Population	1.077	-0.003	1.660	0.063
	(4.584)	(0.449)	(10.465)	(1.040)
Share Black Population	-0.066	-0.005	-0.255*	-0.023*
	(0.058)	(0.006)	(0.131)	(0.013)
Estimator	OLS	OLS	OLS	OLS
N	51	51	51	51
R^2	0.465	0.416	0.369	0.301

Table 5: *Miller Family - Investigation of baseline results*

	Nominal (χ)	Real (baskets)	Nominal (incl. Medicaid)	Real (incl. Medicaid)
	(1)	(2)	(3)	(4)
Constant	28.817	2.278	62.698*	4.516**
	(29.305)	(1.639)	(31.495)	(1.868)
Price Level	0.039***	0.001*	0.031**	0.001
	(0.012)	(0.001)	(0.012)	(0.001)
Democrat (0/1)	8.799***	0.529***	8.709***	0.597***
	(2.819)	(0.158)	(3.030)	(0.180)
Has Income Tax	-4.216	-0.279*	-4.554	-0.283
	(2.781)	(0.156)	(2.989)	(0.177)
Gini Coefficient	-39.760	-3.038	-86.351	-6.158
	(68.084)	(3.807)	(73.174)	(4.340)
Mean Income	-0.549**	-0.020	-0.549**	-0.018
	(0.218)	(0.012)	(0.235)	(0.014)
Share Urban Population	-0.881	-0.090	-0.596	-0.157
	(9.696)	(0.542)	(10.421)	(0.618)
Share Black Population	-0.310**	-0.017**	-0.255*	-0.017**
	(0.121)	(0.007)	(0.130)	(0.008)
Estimator	OLS	OLS	OLS	OLS
N	51	51	51	51
R^2	0.561	0.510	0.486	0.484

Table 6: *Jones Family - Investigation of baseline results*

6 Conclusion

In this paper, we develop a quantitative framework exploring geographic variation in marginal tax rates of low-income households in the United States. The core of this framework is a detailed imputation of the net transfers received by households with distinct demographic characteristics in different states. We combine our imputation model with a careful characterization of the lowest twenty percentiles of each state's income distribution. Together, these elements allows us to overcome the limitations of survey data and to compute a measure of income insurance which reflects the large heterogeneity of disposable incomes in the lower tail of the income distribution. This measure is more appropriate for capturing the dispersion of marginal tax rates and to capture cross-state policy heterogeneity than simple functional forms used by the literature on optimal tax progressivity.

Our results also demonstrate there is considerable variation in the pass-through of earning shocks to disposable income for low-income households. In our baseline analysis, we found that it ranges from 30 to 90%. This variation stems from two sources, namely state level tax and transfer policies as well as differences in nominal income levels. It is unaffected when we take into account state-specific living costs and Medicaid (which is the largest means-tested transfer program in the US). Moreover, it is also prevalent in insurance against job loss.

We find that the variability of marginal tax rates is largely determined by household characteristics. Comparing results pertaining to three different prototype households (married couple, household head, single tax filer) shows that it is largest for households with children while it is much smaller for childless single tax filers. This finding is driven by the observation that most transfer policies, at both the state and federal level, favor households with children with respect to eligibility and generosity. The final part of our analysis identified state attributes which are correlated with differences in state level marginal tax rates and the associated insurance against earning shocks. We establish that states with a larger population of black residents and lower mean incomes provide less insurance in their tax and transfer systems. The opposite applies to states which tax income, have more Democrat leaning voters and higher price levels.

Our findings contribute to the literature on optimal taxation, tax progressivity and the role of state governments in determining taxes and transfers for low-income households. As we provide novel measures on the spatial distribution of income insurance, our results speak to a wide range of structural applications. For example, while a large literature studies state welfare generosity as a driver of household mobility, there is so far no analogous emphasis on insurance differences. Indeed, our results motivate a careful investigation if households with risky incomes sort into states providing more insurance. Finally, while our analysis refrains from imposing specific objectives on the optimal provision of insurance, our findings can inform a theoretical investigation into this aspect. For instance, they can speak to whether state governments aim to insure fractions of earning shocks or seek to guarantee a minimum level of subsistence spending for their poorest residents.

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A The United States: A Heterogeneous Fiscal Federation

In this section we detail the institutional context of the United States, which is characterized by considerable variation in regional economic conditions and subfederal policy choices.

Figure 24 provides a stylized summary of the fiscal relationships between the federal government, state governments and households. Both the federal and state governments raise taxes (τ^f,τ_i^s) from households and make direct transfer payments to them (g^f,g_i^s).[32] The eligibility and benefit parameters of some programs are exclusively determined by the federal government which also provides funding from its own revenues (examples are SNAP, Supplemental Security Income (SSI) benefits and Veterans' Pensions). Some other programs, such as TANF and Medicaid, are mandated by the federal government but administered by state governments. For these programs, states have large leeway to decide on parameters regulating benefits and eligibility. Moreover, they have substantial federal funding contributions, either as block or matching grants. The sum of these federal contributions are denoted by G_i^f.

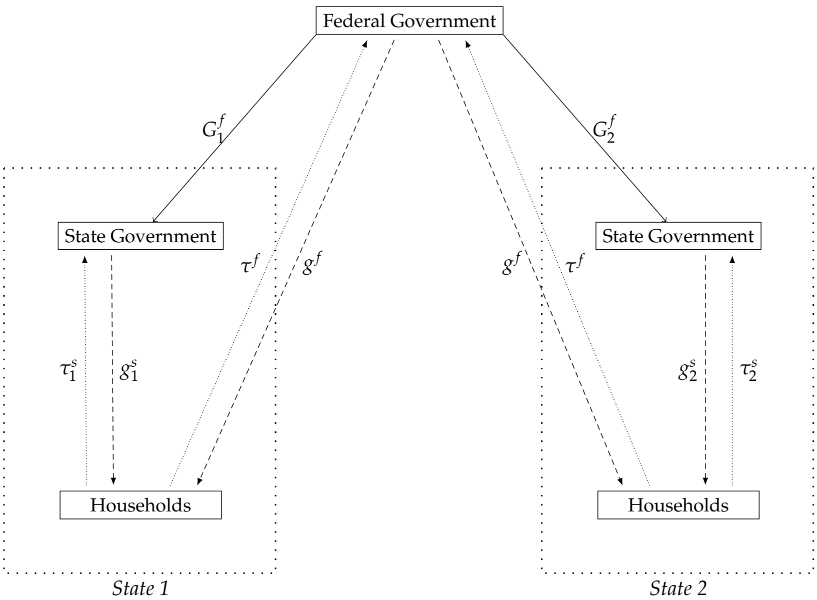

Figure 24: *Fiscal flows between the federal and state governments and households. τ denotes tax schedules, g transfers and G federal grants dedicated to funding transfer programs.*

While state governments have autonomy in designing their tax systems and can adjust their transfer programs according to local conditions and preferences, the federal governments' programs are characterized by a 'uniformity constraint'. The federal income tax code applies to tax filers across the entire US, independent of their state of residence. And the same set of (nominal) parameters determines transfer eligibility and generosity. In contrast to the regional uniformity in federal tax and transfer policies stands variation at the subfederal level, which

[32] Federal personal taxes also include payroll (FICA) taxes which are used to fund the Old-Age and Survivors Insurance programs. As these are entitlement programs we omit their accrued benefits in our analysis which focuses on earnings risk of working age low-income households. Moreover, we also omit indirect taxes which are collected by sub-federal governments, most prominently sales and property taxes.

has three dimensions determining the distribution of real effective marginal tax rates:

1. Regional Variation in Incomes As a measure for cross-state differences in incomes, figure 25 plots the share of tax returns with different amounts of Adjusted Gross Incomes (AGI) as of 2010. As this figure illustrates, in poorer states such as Mississippi, New Mexico, Alabama and Arkansas, the share of filers with AGI below $25,000 is around 45% (or larger) while it is below 30% for richer states like Connecticut. For the intermediate income brackets $25,000 - $50,000 and $50,000 - $100,000, the differences between states are less pronounced. For example, the share of filers in the $25,000 - $50,000 group is close to 23% in all states shown in the figure. For filers with AGI above $200,000, the share again varies noticeably - from about 5% in Connecticut and New Jersey to 1.5% in Mississippi and West Virginia.

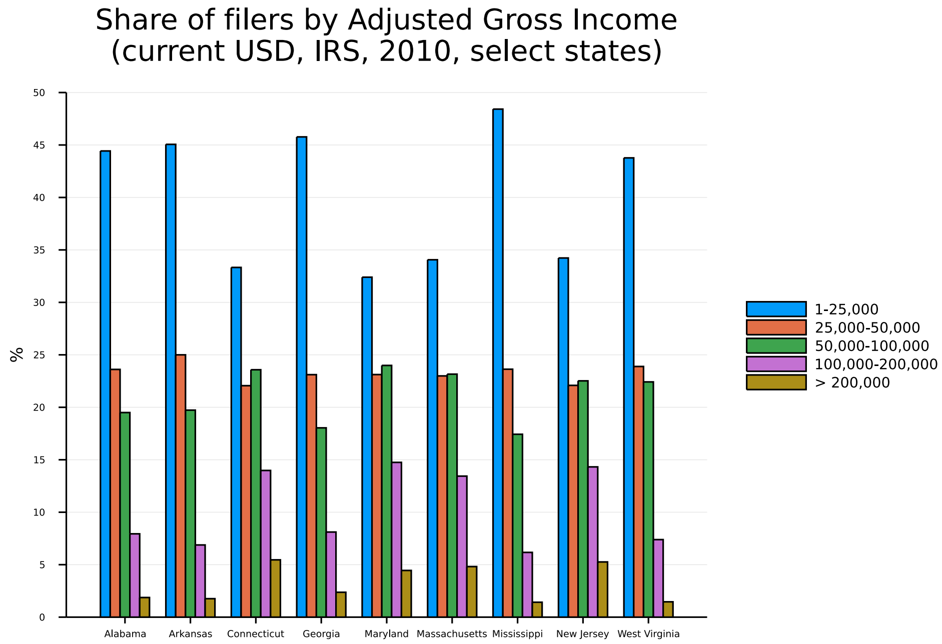

Figure 25: *Share of tax returns with different amounts of Adjusted Gross Income (AGI) in 2010. Source: Internal Revenue Service (IRS).*

These differences imply that the share of households qualifying for different federal income support programs varies by state. For example, Falk (2014b) shows that the share of tax filers participating in the EITC ranged from 12.2% (New Hampshire) to 25.8% (Arkansas) in 2011.

2. Variation in State Tax and Transfer Policies US states enjoy a remarkable degree of fiscal autonomy and their only constraints are (self-imposed) balanced budget requirements. As a result, tax and transfer policies vary widely. Figure 26 highlights the cross state variation in tax policy. While some states raise up to 50% of their personal tax revenue via income taxes, others do not tax income at all. Moreover, while all states tax sales, the corresponding revenue share ranges from about 20% to about 70%. The same is true for property taxes.[33]

[33] Sales and excise taxes include liquor store revenues.

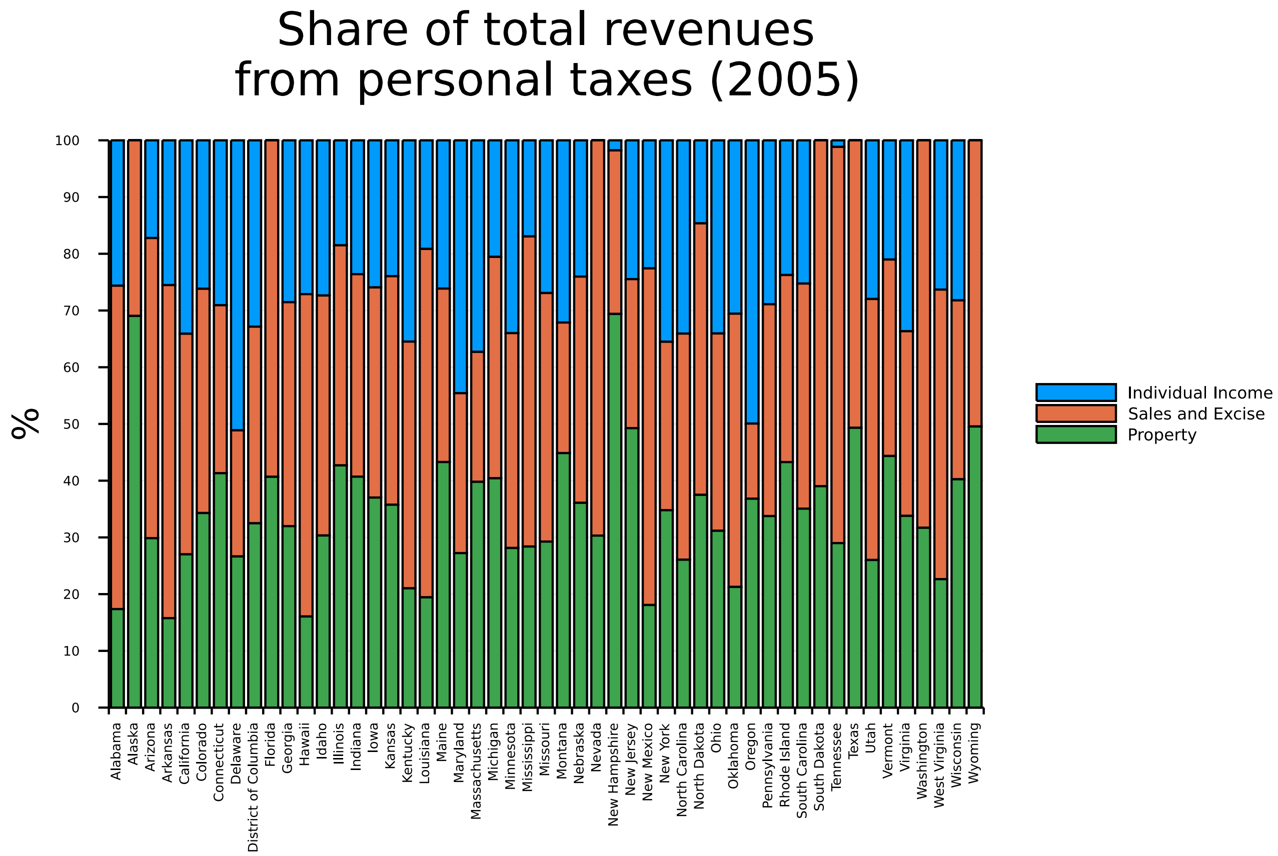

Figure 26: *Income, sales and excise and property taxes as a share of total personal taxes in 2005. Includes states and local governments. Source: Annual Survey of State and Local Government Finances (Census Bureau).*

The heterogeneity in state and local taxes is also mirrored on the spending side. Figure 27 shows the variation in the composition of state and local government spending. Social Services and Income Maintenance includes spending on public welfare, as well as on hospitals, health, employment security administration and veterans' services. The "Other" category includes governmental administration, interest on general debt, transportation, public safety, environment and housing, and general expenditure not elsewhere classified. As this figure shows, the share of spending on welfare and income support programs ranges from about 20% (North Dakota, Nevada) to about 38% (Mississippi, Tennessee).

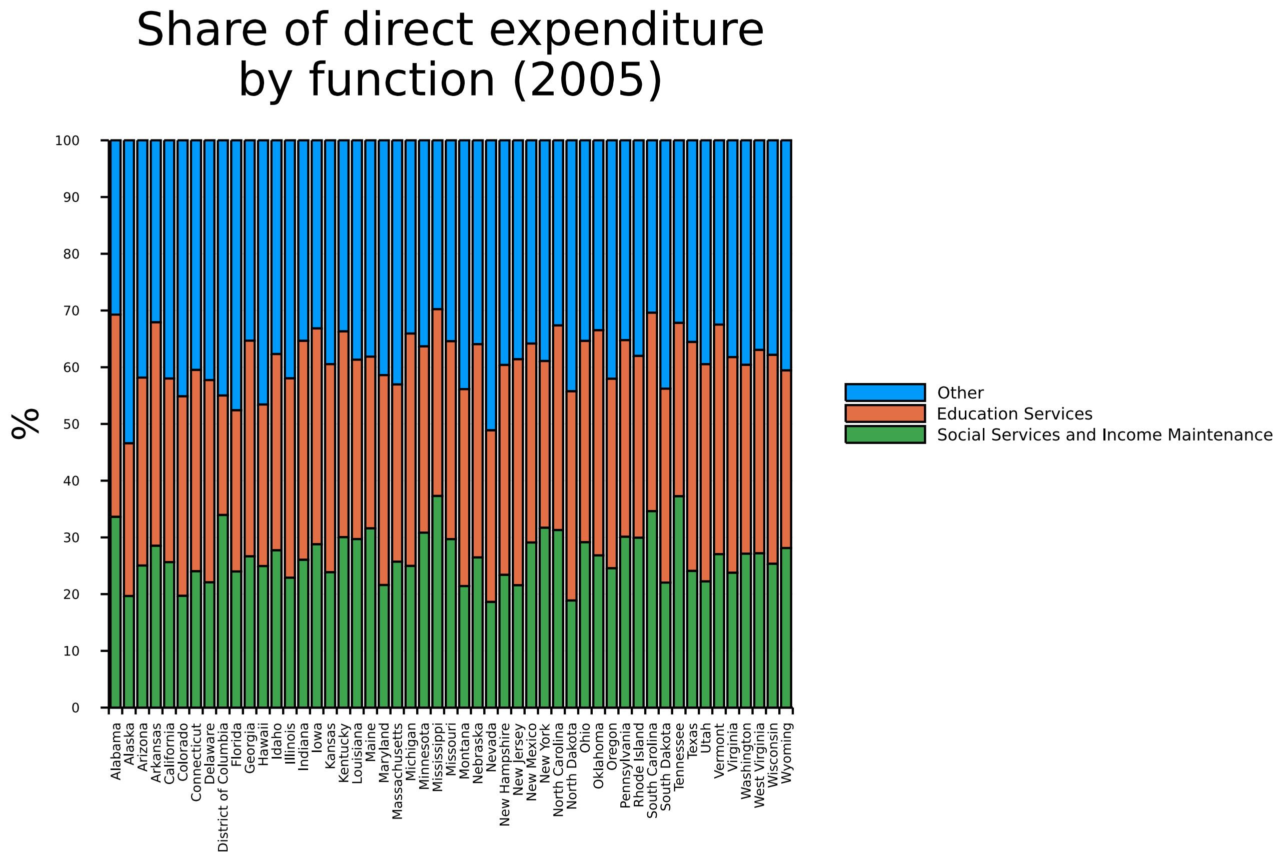

Figure 27: *Expenditure shares of state and local governments by function. Source: Annual Survey of State and Local Government Finances (Census Bureau).*

Moreover, even within 'Social Services and Income Maintenance', there is substantial heterogeneity in how states determine eligibility and generosity of the funds spent in the programs summaized in this category. For two income support programs which have considerable state options, TANF and Medicaid figures 28 and 29 plot state-specific measures of eligibility and generosity.

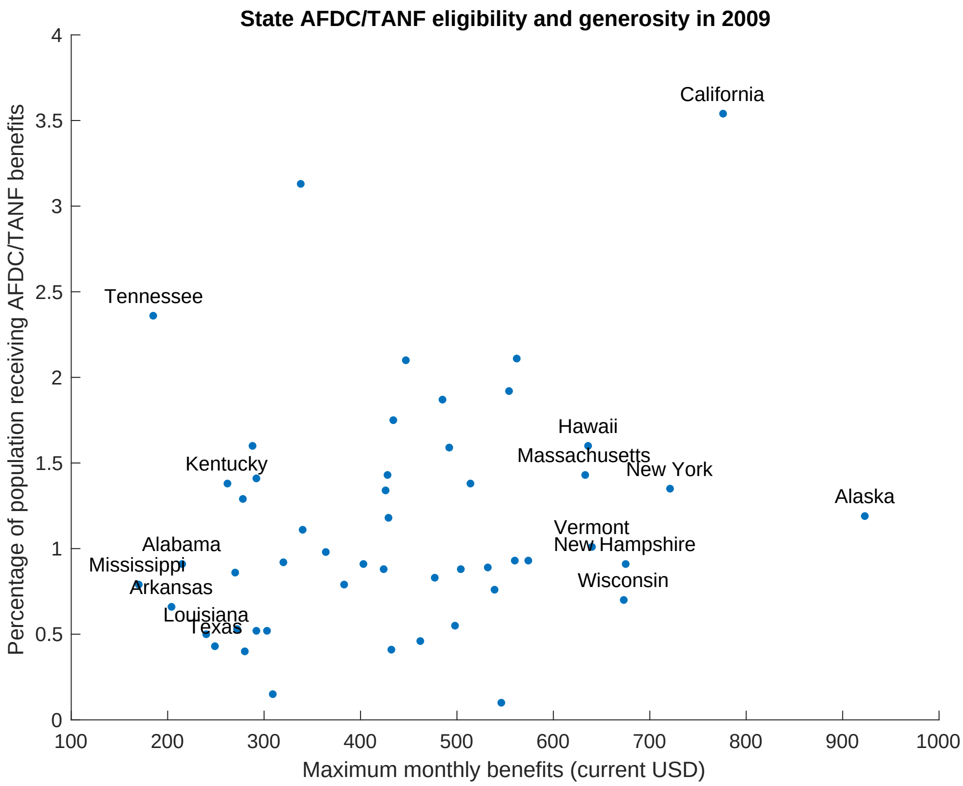

Figure 28: *Eligibility and Generosity of the TANF program (as of 2009*

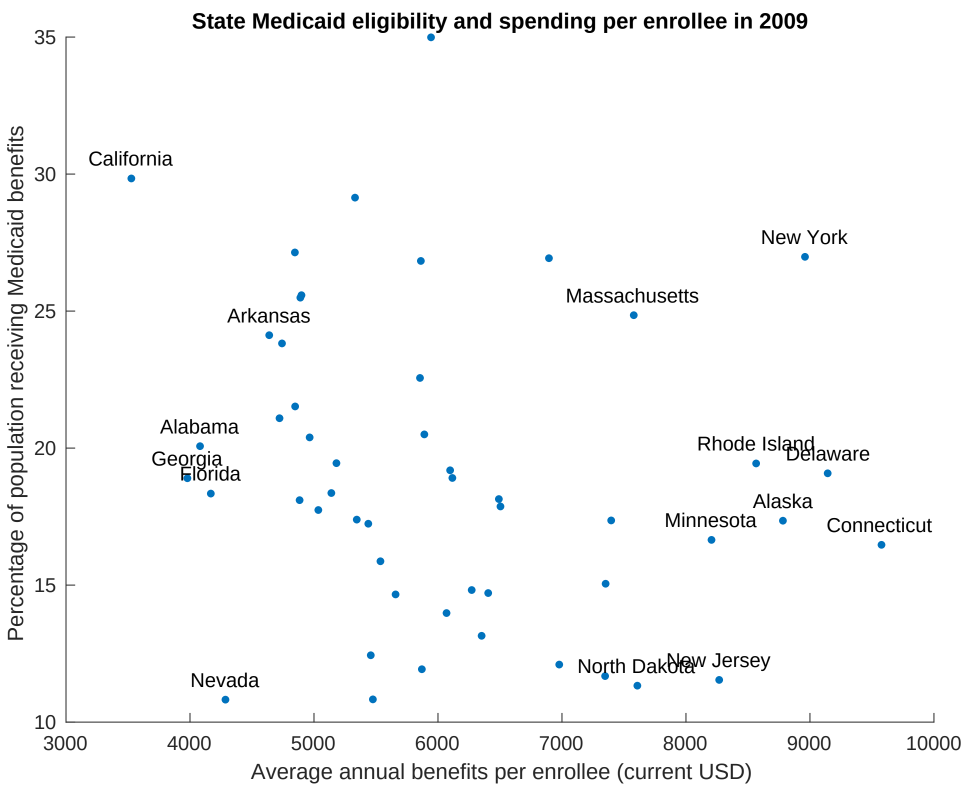

Figure 29: *Eligibility and Generosity of the Medicaid program (as of 2009*

3. Variation in Price Levels The variability of local economic conditions across states also materializes in price levels. Figure 30 shows the states with the lowest and highest living costs as measured by regional price parities compared to the US average. The price level faced by households in Hawaii is almost 20% higher than the national average, whereas that faced by households in Mississippi and Alabama is almost 15% lower than the average. These discrepancies introduce considerable variation in the *real* welfare impact of federally administered policies which have fixed nominal values.

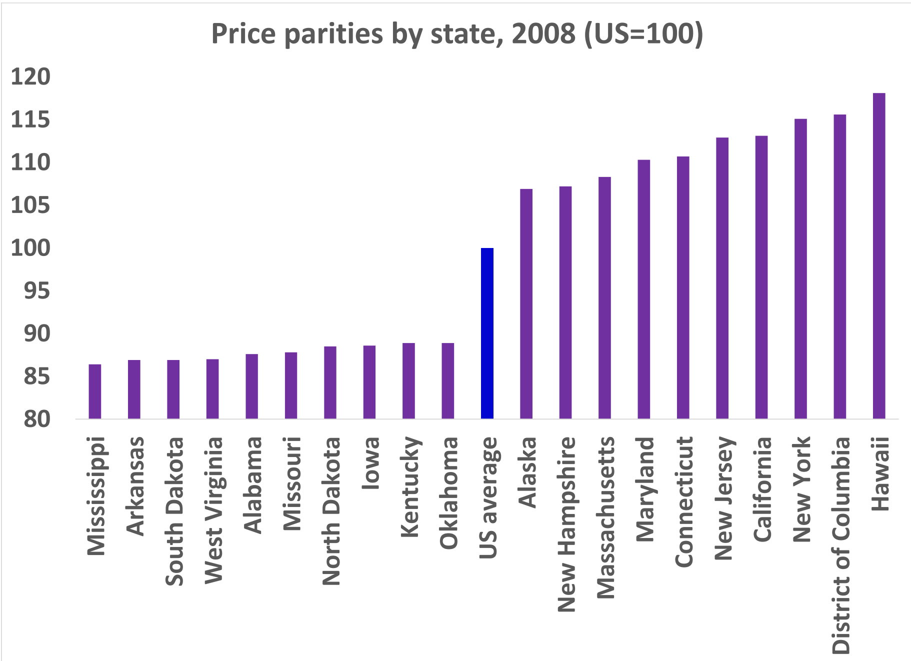

Figure 30: *Regional Pricing Parities by state 2008, 10 highest and 10 lowest. Source: Bureau of Economic Analysis.*

B Shock Size

In our analysis, we apply a transitory shock of 50% to earned income, i.e. we reduce it by half and study the response of taxes and transfers to this change. We choose this size based on findings of Guvenen et al. (2021) who report the dispersion of one-year earnings growth rates from administrative income data. Their base sample includes low income earners which makes their results suitable to study the earnings risk our prototype families are exposed to.[34] In their figure C1 (page 51), they report that the average one year (log) change in earnings in the age group 35 to 44 is about 0.71. In levels of logs, we can write the income evolution of individual

[34] "First, in order for an individual-year income observation to be admissible to the base sample, the individual (i) must be between 25 and 60 years old (the working lifespan) and (ii) have earnings above the minimum income threshold $Y_{min,t}$, that is equivalent to one quarter of full-time work (13 weeks at 40 hours per week) at half of the legal minimum wage in year t (e.g., approximately $1,885 in 2010)."

i as

$$\log(y_{t+1}^i) - \log(y_t^i) = \delta \tag{15}$$

$$y_t^i = \frac{y_{t+1}^i}{\exp(\delta)} \tag{16}$$

Using $\delta = 0.71$ results into

$$y_t^i = \frac{y_{t+1}^i}{2.03} = y_{t+1}^i \times 0.49 \tag{17}$$

Thus, a shock size of about 50% is a suitable measure to represent the risk due to unpredictable transitory earnings changes faced by our population of interest.

C Income Taxation in the US

C.1 Federal

In this section, we provide a number of definitions relating to the US federal income tax code, the role of deductions, exemptions and tax credits in particular. As they differ for demographic characteristics of the tax filer, they are key determinants of the federal taxes imputed for our prototype households.

Adjusted Gross Income versus Gross Income

$$\text{Adjusted Gross Income} = \text{Gross Income} - \text{Adjustments} \tag{18}$$

where Adjustments include items such as educator expenses, student loan interest, alimony payments or contributions to a retirement account. We assume these are zero for our prototype households. Thus, the incomes we construct for the lowest twenty percentiles in each state and year are equal to Adjusted Gross Income (AGI).

Deductions and Exemptions

$$\text{Taxable Income} = \text{Adjusted Gross Income} - \text{Deductions} - \text{Exemptions} \tag{19}$$

The US federal income tax code allows tax filers to choose a standard deduction or deduct a select number of itemizable expenses.[35] As TAXSIM also checks if a filer is better off by itemizing or taking the standard deduction, our simulation captures this aspect of the federal income tax code.[36] However, as figure 31 illustrates, the share of itemizers among our population of interest was below 20% in all states in 2006 and increases steeply in AGI. The reason is that tax filers with low incomes generally do not have itemizable expenses which exceed the standard deduction.[37] Note that the upper cutoff of the lowest income group in the IRS data is still (much)

[35] The standard deductions differ by tax filing status. For example, in 2006, it was $5,150 for a single filer, $10,300 for a married joint filer and $7,500 for a head of household filer.

[36] TAXSIM also considers the deduction phaseout.

[37] Itemizable expenses are property taxes, mortgage interest, state and local sales and income taxes as well as contributions to retirement savings accounts.

larger than the incomes we focus on in our analysis. Moreover, the IRS data include incomes of retirees who typically have large (itemizable) property tax liabilities while our prototype filers are renters of working age. Thus, the shares displayed in figure 31 are upper bounds for our population of interest and their true shares are presumably much lower. For that reason, our prototype filers can be assumed to always choose the standard deduction.

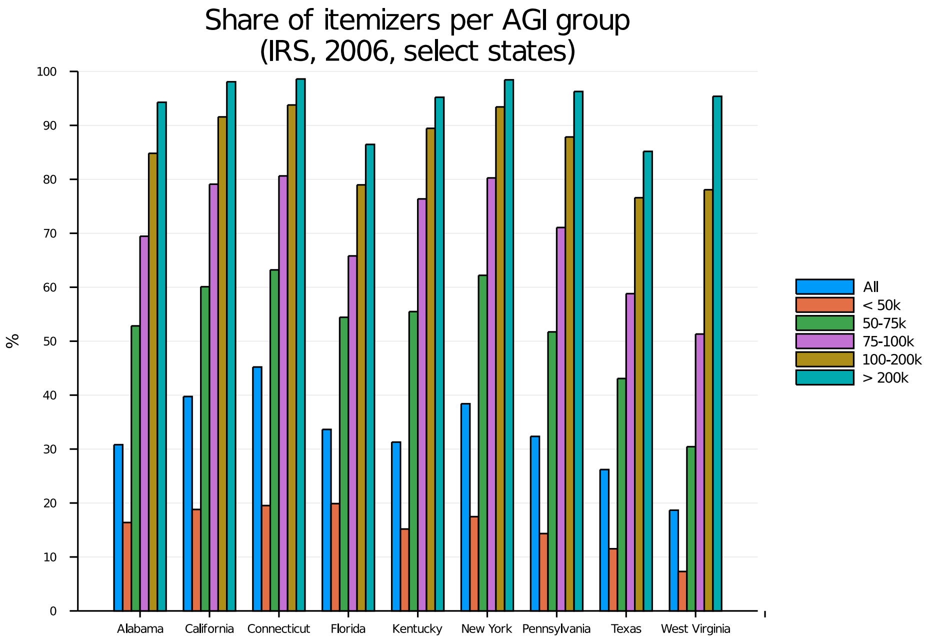

Figure 31: *Share of itemizers in different states and income levels*

Tax filers can claim an exemption for themselves, their spouse (for married couples filing jointly) as well as a qualifying child or relative. In 2006, each exemption was worth \$3,300. As for deductions, TAXSIM computes the entitled total exemption amounts for each tax filer and also considers the exemption phaseouts.[38]

Tax Credits

$$\text{Income Tax Liability} = \text{Tax on Taxable Income} - \text{Tax Credits} \tag{20}$$

Tax credits may exceed the amount of taxes owed. In such cases, tax filers are entitled to refundable tax credits (as they have a negative tax liability). The two most important of these credits are the Earned Income Tax Credit (EITC) and the Child Tax Credit (CTC) both of which are accounted for by TAXSIM.

The EITC is fully refundable and its structure is displayed in figure 32 where $\overline{eitc}$ refers to the maximum EITC amount, cr and pr denote the phase-in (credit) rate and phase-out rate, respectively. $\underline{y}$ denotes the minimum gross income for the maximum EITC credit while $\widetilde{y}$ and

[38]The incomes of our population of interest are well below the beginning of this phaseout.

$\overline{y}$ denote the begin and end of the phase out range. Tax filers with gross income larger than $\overline{y}$ are not eligible to the EITC.

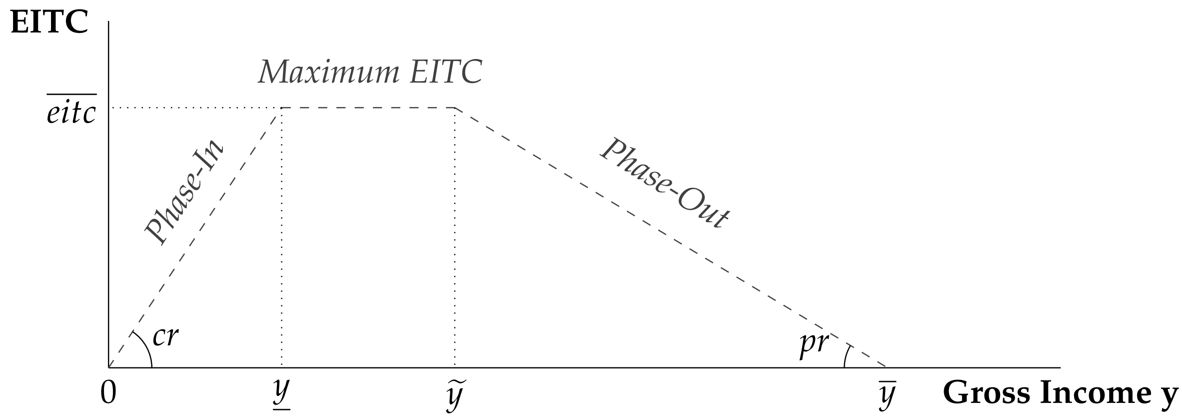

Figure 32: *Parameters of the Earned Income Tax Credit (EITC)*

The amounts of these parameters differ by tax filer type as well as number of dependents.[39] While these policy parameters are updated periodically, they do not take into account differences in local incomes or price levels. In other words, the fraction of tax filers eligible for the EITC as well as the real value of its benefits differs by state (and year).

C.2 State

In this section, we use information from Duncan (2005), Sammartino and Francis (2016) and various reports of the Tax Foundation to summarize the most important features of state income tax systems. In table 7, we compare their four elements which have the strongest repercussions on cross-state differences in income tax progressivity. Column one lists state definitions of taxable income. 42 of 51 states (including Washington DC) levy income taxes and follow one of three taxable income definitions: i) Federal Adjusted Gross Income (27) ii) Federal Taxable Income (10) iii) Other (Alabama, Arkansas, Mississippi, New Jersey, Pennsylvania).

Column two shows whether a state allows to deduct federal income taxes paid. In these eight states, higher federal tax payments reduce the state tax liability. Using information from Levitis and Koulish (2008), column three indicates if a state has an earned income tax credit, and if so whether it is refundable. For example, during our entire simulation period, DC had a refundable EITC which was a (changing) fraction of the federal EITC while Illinois switched from non-refund to refund. Maine, on the other hand, always had an EITC but it was never refundable. Importantly, TAXSIM accounts for these differences carefully.[40] The final column of table 7 gives a rough measure for the progressivity of state income taxes. In this column, we show the lowest and highest marginal tax rate of each state's income tax. In general, larger top rates (and larger gaps between highest and lowest rates) indicate larger progressivity.

[39] For example, in 2006, the maximum EITC of a tax filer claiming two children as dependents was $4,536, while it was $412 for tax filers without children as dependents. For the income of the the phase-out begin, the values were $14,810 and $6,740.

[40] See here: `https://users.nber.org/~taxsim/state-eitc.html`

State	Taxable Income	Federal Income Tax Deductible	State EITC (as % of federal EITC)		Marginal Rate	
			Refundable	*Non Refundable*	*lowest*	*highest*
Alabama	*other*	yes			2%	5%
Alaska*	No income tax	no				
Arizona	Federal AGI	no			2.87%	5.04%
Arkansas	*other*	no			1%	7%
California	Federal AGI	no			1%	9.3%
Colorado	Federal TI	no			4.63%	
Connecticut	Federal AGI	no			3%	5%
Delaware	Federal AGI	no			2.2%	5.96%
District of Columbia	Federal AGI	no	35%		5%	9%
Florida*	No income tax	no				
Georgia	Federal AGI	no			1%	6%
Hawaii	Federal TI	no			1.4%	8.25%
Idaho	Federal TI	no			1.6%	7.8%
Illinois	Federal AGI	no	5%		3%	
Indiana	Federal AGI	no	6%		3.4%	
Iowa	Federal AGI	yes		6.5%	0.36%	8.98%
Kansas	Federal AGI	no	15%		3.5%	6.45%
Kentucky	Federal AGI	no			2%	6%
Louisiana	Federal AGI	yes			2%	6%
Maine	Federal AGI	no		4.92%	2%	8.5%
Maryland	Federal AGI	no	20%		2%	4.75%
Massachusetts	Federal AGI	no	15%		5.3%	
Michigan	Federal AGI	no			3.9%	
Minnesota	Federal TI	no	yes		5.35%	7.85%
Mississippi	*other*	no			3%	7.85%
Missouri	Federal AGI	yes			1.5%	6%
Montana	Federal AGI	yes			2%	11%
Nebraska	Federal AGI	no			2.56%	6.84%
Nevada*	No income tax	no				
New Hampshire*	No income tax	no				
New Jersey	*other*	no	20%		1.4%	8.97%
New Mexico	Federal AGI	no			1.7%	6.8%
New York	Federal AGI	no	30%		4%	7.7%
North Carolina	Federal TI	no			6%	8.25%
North Dakota	Federal TI	no			2.1%	5.54%
Ohio	Federal AGI	no			0.74%	7.5%
Oklahoma	Federal AGI	yes	5%		0.5%	6.65%
Oregon	Federal TI	yes		5%	5%	9%
Pennsylvania	*other*	no			3.07%	
Rhode Island	Federal AGI	no	10%	25%	3.75%	9.9%
South Carolina	Federal TI	no			2.5%	7%
South Dakota*	No income tax	no				
Tennessee*	No income tax	no				
Texas*	No income tax	no				
Utah	Federal TI	yes			2.3%	7%
Vermont	Federal TI	no	32%		3.6%	9.5%
Virginia	Federal AGI	no			2%	5.75%
Washington*	No income tax	no				
West Virginia	Federal AGI	no			3%	6.5%
Wisconsin	Federal AGI	no	4/14/43%		4.6%	6.75%
Wyoming*	No income tax	no				

Table 7: *State tax policy parameters as of 2005; Minnesota: has a "working family tax credit" with elaborate parameters independent of the federal EITC. Wisconsin: 1/2/3+ number of dependents. Source: TAXSIM documentation, Tax Foundation, Duncan (2005)*

D Federal and State Transfer Programs

D.1 SNAP

To impute benefits of the transfer program "Supplemental Nutrition Assistance Program" (SNAP, formerly "Food Stamps"), we obtain the historical program parameters for the years 2000 to 2007 from various editions of the "Food Stamp Program Participation Rates" and "Trends in Supplemental Nutrition Assistance Program Participation Rates" reports, for example Leftin (2010). Moreover, we follow Moffitt (2016), the chapter by Hoynes and Schanzenbach (2015) in particular, as well as the comprehensive summaries and benchmark imputations presented in Hoynes, McGranahan, and Schanzenbach (2014) and Tremblay (1994) to design the imputation program. Finally, we consulted Aussenberg (2014), Wilde (2001) and Hanson and Andrews (2009) to assess the quality of the imputed benefits and to account for the interaction of SNAP eligibility and other transfer programs ("categorical eligibility").

In general, as SNAP is a federal program, the importance of state parameters for eligibility and generosity is minor. In fact, they mostly result in marginally different definitions of countable assets in the means test. However, as we assume that our prototype tax filers have zero assets, i.e. are hand to mouth, we omit this aspect.

Eligibility SNAP eligibility refers to the household unit. Specifically, SNAP regulations define the unit for which eligibility needs to be established as consisting of all household members "who purchase and prepare food together". Any household has to meet three criteria to be considered eligible:

1. Gross monthly household income has to be below or equal to 130% of the (monthly) Federal Poverty Level (FPL).[41]
2. Net monthly household income (i.e. income after specified deductions) has to be below or equal to the FPL.
3. Countable assets may not exceed a certain amount.

Of these three eligibility rules, we account for 1. and 2. but abstract from 3. for the reasons mentioned above.

Benefits Conditional on eligibility, SNAP benefits are assigned given this formula

$$\begin{aligned}\text{SNAP Benefit}_{i,t} &= \text{Maximum Benefit}_t \\ &\quad - \text{Benefit Reduction Rate}_t \times \text{Net Income}_i \end{aligned} \tag{21}$$

The maximum benefit is designed to cover monthly food expenditures of families with different

[41] While the term FPL is used frequently, this measure actually refers to the 'Poverty Guidelines' (PG). These guidelines are published as current US Dollar amounts for varying family sizes each year in the Federal Register by the Department of Health and Human Services (HHS). Note that different PGs apply for Alaska and Hawaii to account for the higher cost of living in these two states. We account for these details in designing the imputation program.

sizes as established by the Thrifty Food Plan (TFP).[42] Following the official program definitions, we establish SNAP net income as

	cash pre-tax income	(1)
–	standard deduction	(2)
–	20% deduction of earned income	(3)
–	excess shelter cost deduction	(4)
–	deduction for childcare costs associated with working and training	(5)
–	medical cost deduction for elderly and disabled	(6)
=	net income	(7)

Given the assumptions regarding our prototype tax filers, we do not consider items (4), (5) and (6).[43] Our imputation includes the 20% deduction (3) as well as the standard deduction (2). Moreover, our imputation carefully considers the fact that SNAP regulations define cash pre-tax income listed in (1) to exclude in-kind benefits and tax credits. In other words, (1) does not include Medicaid, state and federal earned income as well as child tax credits. It does, however, include include cash transfers such as TANF and unemployment benefits.

Finally, our imputation program uses the official (and time invariant) benefit reduction rate of 0.3. Moreover, as for all other tax and transfer benefits, we assume a take up rate of 100% to have a measure of the statutory rates and a consistent emphasis on estimates which reflect upper bounds of policy generosity.

D.2 TANF

Hoynes and Luttmer (2011) collected information on eligibility and benefits of the transfer programs "Temporary Assistance for Needy Families" (TANF) and used it to impute TANF benefits for PSID observations.[44] We use the same calculator to impute TANF benefits for our prototype tax filers and we cordially thank Hilary Hoynes for sharing it with us. The appendix of Hoynes and Luttmer (2011) provides details on the calculator so we briefly summarize the main state parameters of the TANF program in what follows.[45]

[42]"Benefits are tied to the cost of a "market basket of foods which if prepared and consumed at home, would provide a complete, nutritious diet at minimal cost", the so-called Thrifty Food Plan, (...)." Moffitt (2016), page 226. TFP costs are provided by the US Department of Agriculture and are a key policy measure in setting nutritional cost standards. Note that Congress can choose to increase maximum benefits above the TFP level during economic downturns. This was one element of the American Recovery and Reinvestment Act of 2009. However, this decision was not taken during our period of interest.

[43]Recall that the three kinds of filers we consider are neither homeless, have no considerable childcare costs and do not have any disabled or elderly dependents.

[44]Prior to welfare reform in 1996, this program was called "Aid to Families with Dependent Children" (AFDC). Under this earlier program, state policy makers enjoyed much less freedom to adjust program parameters.

[45]For example, the appendix of Hoynes and Luttmer (2011) shows that imputed TANF benefits compare favorably with administrative data and other studies. Importantly, as we do for other taxes and transfers, the calculator assumes a uniform take-up rate of 100%. Finally, as the calculator only covers years until 2005, we assume that TANF benefits increase by 2% per year and keep all other parameters constant.

The formula assigning TANF benefits to households i in year t in state s is given as:

$$\begin{aligned}\text{TANF Benefit}_{i,t,s} = &\ \text{Maximum Benefit}_{t,s} \\ &- \text{Benefit Reduction Rate}_{t,s} \times \left(\text{Earned Income}_{i,t,s} - \text{Earnings Disregard}_{t,s}\right) \\ &- \text{Unearned Income}_{i,t,s} \end{aligned} \tag{22}$$

Hence, state specific regulations regarding eligibility and generosity of the TANF program materialize through state (and year) differences in the earnings disregard, the benefit reduction rate and the maximum benefit. As for all other tax and transfer benefits, we assume a take up rate of 100%.

Several studies demonstrate that state policy makers have broad discretion in using TANF funds. Schott, Pavetti, and Floyd (2015) summarizes the consequences as follows: "In some cases, states have used TANF and MOE funds to expand programs, such as state Earned Income Tax Credits (EITCs) or pre-K, or to cover the growing costs of existing services, such as child welfare. In other cases, they have used TANF/MOE funds to replace existing state funds, thereby freeing those state funds for purposes unrelated to providing a safety net or work opportunities for low-income families." (p. 3). Moreover, Hahn et al. (2017) and Falk (2014a) found that these discrepancies have been growing over time.

Unlike SNAP, TANF transfers have a federal and state funding component. Federal funding contributions are provided as block grants. The state specific magnitudes of these grants was determined during welfare reform of 1996 and related to a state's historical spending on TANF's predecessor (Aid to Families with Dependent Children, AFDC). Hence, historical state discrepancies on welfare spending perpetuated into TANF and became permanent. Moreover, since per capita AFDC spending varied greatly across states, the relative size of the TANF block grants differ substantially. In addition, federal TANF grant blocks have not been adjusted ever since so the federal funding of TANF is invariant with respect to changing economic conditions, the number of household in need of assistance specifically. As an illustration of the consequences of this decision, Hahn et al. (2017) report that "The average TANF block grant per child living in poverty is \$1,190, ranging from \$293 in Texas to \$3,154 in Washington, DC."

To account for these differences in state and federal funding for TANF, we compute the federal share f_s^{TANF} for each state s using program data from the Office of Family Assistance (OFA) website.[46] The resulting federal shares range from 29% (Washington) to 83% (West Virgina) with a mean (median) of 59% (60%). We use them to compute state and federally funded TANF benefits as

$$\text{State TANF Benefit}_{i,t,s} = (1 - f_s^{TANF}) \times \text{TANF Benefit}_{i,t,s} \tag{23}$$

$$\text{Federal TANF Benefit}_{i,t,s} = f_s^{TANF} \times \text{TANF Benefit}_{i,t,s} \tag{24}$$

[46] `https://www.acf.hhs.gov/ofa/programs/tanf/data-reports` Specifically, we obtain figures on federal and state assistance and non-assistance expenditures from the "TANF Financial Data - FY 2010" spreadsheet. For 2010, total expenditures are in table B.1., total federal spending is in C.1.a. and state spending in C.2.a.

Finally, to evaluate if our married prototype tax filer would receive any TANF benefits, we find the by state and year restrictions applying to two-parent non-disabled TANF applicants from Table L2 of Kassabian et al. (2013) and use this information to augment the calculator of Hoynes and Luttmer (2011) who only impute TANF benefits for single parent families. Given our assumptions on the work history of parents, our prototype families meet all work related requirements. Moreover, we abstract from the waiting period (which would apply in only two states, Maine and Kentucky) but take into account that two-parent, non-disabled families are not TANF eligible in North Dakota. Lastly, as specified in Kassabian et al. (2013), we use the income of both spouses towards the TANF earned income eligibility test.

D.3 Medicaid and CHIP

Medicaid is a federally mandated program requiring states to support low-income households in obtaining medical treatment. The Children's Health Insurance Program (CHIP) program targets children in families with incomes which are above the eligibility threshold for Medicaid but too low to afford private insurance. Thus, unlike SNAP and TANF, these programs only insure medical expenditures but do not stabilize disposable incomes. However, they are the largest means-tested transfer programs in the US and have considerable state options with respect to eligibility and generosity. In fact, the Medicaid expansion during the years 1984 to 1993 has resulted in profound cross-state heterogeneity in eligibility and services covered of this program. The introduction of CHIP in 1997 has exacerbated these differences even further. Therefore, we do not include them in our baseline analysis but study their effects in a separate extension.

As Medicaid and CHIP benefits cannot be imputed using a simple benefit formula (as for SNAP and TANF), Hoynes and Luttmer (2011) developed an imputation program which includes state and year specific eligibility parameters for child age and family income thresholds.[47] Average benefits for children and families are established from administrative data on average expenditures per adult and child by state and year. As for TANF, we use the provides details on the calculator. We adjust the imputation to assume a uniform take up rate of 100% (Hoynes and Luttmer (2011) assumed that the take-up rate for eligible children varies by year). Moreover, as a specific feature of Medicaid is that categorical eligibility results from being eligible for TANF, our imputation accounts for this form of eligibility.

Medicaid and CHIP are funded from state funds and federal matching grants. State specific federal grants are determined by the Federal Medical Assistance Percentage (FMAP). For each year (t), these rates are determined from state (s) income relative to national (US) income using this formula

$$\text{FMAP}_{s,t} = \max\left\{\frac{\text{Per capita income}^2_{s,t}}{\text{Per capita income}^2_{US,t}} \times 0.45, 0.5\right\} \tag{25}$$

Hence, states with lower relative per capita income receive more generous federal matching grants for their Medicaid expenditures. Figure 33 shows the cross-state FMAP variation in 2000

[47] Pregnancy eligibility is also accounted for by their calculator. However, we assume that our prototype tax filer households do not qualify according to this criterion.

and 2007. As illustrated in this figure, FMAPs range from 50% in richer states to about 75% in poorer states. Thus, to split Medicaid benefits into state and federal shares (as for TANF), we use FMAP rates for each state and year.

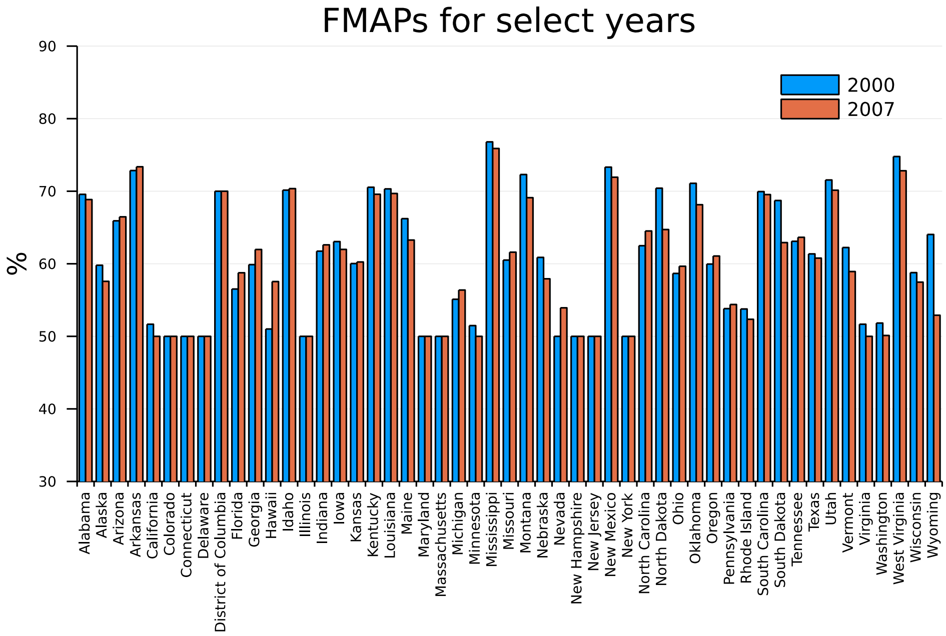

Figure 33: *Medicaid Federal Medical Assistance Percentage (FMAP) for select years*

E Unemployment Insurance Benefits

According to the "Comparison of State Unemployment Laws" (various years) of the US Department of Labor, there are six significant state policy parameters determining unemployment benefits (UB):

1. The wages and employment needed in a "base period" to be considered eligible for UB payments
2. The period during which UB may be collected ("benefit year")
3. The amount payable for a week of total or partial unemployment ("replacement rate")
4. Dependent allowances
5. Waiting periods[48]
6. The maximum amount of regular UB which a worker may receive in a benefit year

To account for this rich variation, we extend the approach of Low, Meghir, and Pistaferri (2010) in constructing our imputation program. Thus, as their calculator, we assume that our prototype tax filers meet the state specific base periods and other work history requirements to

[48]Some states have mandatory waiting periods expressed in weeks. During this period, eligible workers cannot receive UB. "A waiting week occurs during the first week of a new spell of unemployment when a jobless worker satisfies all the requirements for eligibility, but does not receive any benefit payment for his/her first week of unemployment." (`https://www.nelp.org/wp-content/uploads/2E-Avoiding-Waiting-Weeks.pdf`)

qualify (1). However, we go beyond their imputation approach in several dimensions. First, we provide a careful characterization of UB amounts payable, i.e. we carefully approximate the state specific replacement rate while they assume a fixed rate of 75% (3). Second, we account for state differences in dependent allowances (4). Third, we include state specific waiting periods (5). Moreover, as we are interested in the UB available shortly after job loss, we abstract from benefit year restrictions (2) but account for maximum UB amounts per benefit year (6). As for tax credit and transfer benefits, we take this decision to show the state unemployment insurance systems in their most generous view.

In summary, we study UB variation due to items 3, 4, 5 and 6. In our view, these features are the most relevant sources of heterogeneity determining the amount of insurance provided to our prototype tax filers upon receiving a shock reducing their earned income to zero. Accordingly, we assign weekly UI benefits to our prototype tax filers i residing in state s in year t according to

$$UB_{i,s,t} = \max\left(\min\left(\overline{b}_{s,t}, b_{s,t}(w_{i,t-1})\right), \underline{b}_{s,t} \right) \tag{26}$$

where $\overline{b}_{j,t}$ denotes the weekly maximum benefit ('cap') while $\underline{b}_{j,t}$ represents the weekly minimum benefit. $b_{s,t}$ is the replacement formula which determines the weekly benefits (within the boundaries of the minimum and maximum amounts). The input to this benefit formula is $w_{i,t-1}$ which is the wage earned by the claimant in the past quarter. Finally, after considering waiting periods, our imputed monthly benefits are:

$$UB^{m}_{j,t} = (4 - WP_{j,t}) \times UB_{j,t} \tag{27}$$

Hence, our imputation requires state and year specific values for maximum and minimum UB, waiting periods and, most importantly, a reasonable approximation of the benefit formula. We obtain these from the chapter "Monetary Entitlement" of the "Comparison of State Unemployment Insurance Laws" reports.[49] Maximum and minimum benefits are easy to collect from the table "Weekly Benefit Amounts". From the same table, we use the information in the column "Method Of Calculating & Formula" to approximate the replacement rate as a percentage of a claimants previous wage w prior to becoming unemployed. In general, these rates can be a fixed percentage of the wage during the base period (for example, in most states this rate is 1/26, i.e. about 3.85%), while other states select highest (or lowest) waves, or add weighted averages of quarterly wages during the base period.[50]

As some states augment the weekly benefit by a dependent's allowance, we also design the imputation program to allow for a different number of dependents which requires to account for two aspects: First, the definition of a a dependent. Second, their maximum number. Regarding the former, the reports explain that "All States with dependents' allowances include children

[49] Available from the US Department of Labor: `https://oui.doleta.gov/unemploy/comparison/`

[50] We collapse all the different methods (HQ, MQ, AW, WW) by assuming that the work history of the claimant is such that they have received the same weekly income over a number of weeks sufficient to meet the base period requirements as outlined above. This simplifies the benefit formula substantially while preserving the differences in payable amounts.

under a specified age (...). In some states children are the only dependents recognized". Therefore, we treat the children of our prototype tax filers as qualifying for the dependent allowance. Finally, to limit the number of dependents the two parent tax filers can claim, we only allow one of them to claim the two children as dependents.[51]

F State Price Measures

Our aim is to construct a price measure for necessity expenditures of lo- income households by state and year. Using data from the Consumer Expenditure Survey, we find that the largest consumption spending share of these households are food at home and housing. As illustrated by figure 34, this share constitutes about 55% of their total expenditures. No other income group has to dedicate such a large amount of spending towards this particular two categories. Thus, we use food and rental expenditures as the two components of our price measure.

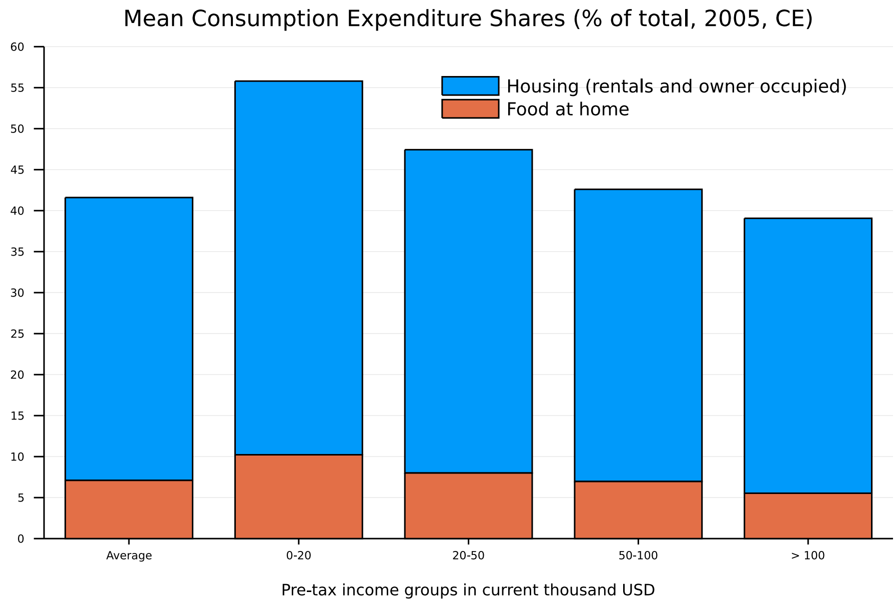

Figure 34: *Mean spending shares on food and housing of different income groups according to the Consumer Expenditure Survey (CE)*

We construct the food component of the state price measure using the methodology outlined in Gregory and Coleman-Jensen (2013) and applied in Bronchetti, Christensen, and Hoynes (2019). This methodology estimates the purchase price, for different US regions, of the Federal government's Thrifty Food Plan (TFP), which specifies the minimum consumption of different food types necessary for achieving a nutritious diet. This is achieved by using the Quarterly Food at Home Price Database (QFAHPD) to derive prices for each of the food types included in the TFP. The QFAHPD uses Nielsen Homescan data to calculate quarterly food prices for over 50 food groups in 30 different regions or 'market groups'. Since the TFP specifies consumption

[51] In practical terms, this means we give this family one amount regular benefits plus one amount of benefits including two dependents. For the latter, we still apply the min and max benefit restrictions. For the married prototype household, we assume that both spouses lose their jobs simultaneously. Hence, we abstract from any working or non-working spouse allowances and treat both of them as insured.

individually for each potential member of a household (e.g. adult male, adult female, child of a given age), we can construct the relevant food basket for each of our household types. This approach therefore allows us to capture variation in the price of food purchases by region and by household composition.

One obstacle to using this approach is that the market groups for which the QFAHPD is provided do not correspond to US states. We therefore need to find a way to assign prices from market groups to states. Fortunately, the data set includes information on which US counties are contained in each of the market groups. These counties can then be assigned to US states based on their Federal Information Processing Standard (FIPS) codes.

We combine this with information on the estimated population of each of the counties from the Census Bureau County Intercensal Tables, for each year between 2000 and 2008. This allows us to determine, for a given state and year, what proportion of the population of that state lived in each market group. Then, for a given state, year and household type, the food basket price is a population-weighted average of the prices calculated for the market groups which contain households from that state. For example, for Florida in the year 2000, we find that 39% of the population lived in market group 7 'North Florida', 47% lived in group 17 'South Florida', and 14% lived in group 95 'NonMetro South Atlantic'. The food basket price for Florida in 2000 is therefore a weighted average of the prices for these three market groups, with the weights given by the population percentages.[52]

To construct year, state and household type specific rental expenditures, we use data on the 'Fair Market Rent' (FMR) provided by the Office of Policy Development and Research of the US Department of Housing and Urban Development (HUD). The FMR represents the 40th percentile of the distribution of monthly rents of all units occupied by recent movers in a specified geographic area, including US states. As we are interested to estimate rent expenditures of households with low incomes, this measure is a suitable candidate for us. To reflect differences in the number of household members of our prototype families, we leverage that the FMR is provided for rental units with distinct number of bedrooms. Specifically, for the married couple, we use the mean of one and two bedroom apartment rents while we use zero and one bedroom apartments for the household head and the single filer.

Figure 35 displays state averages of our final price measure.

[52] In some cases, missing prices in the QFAHPD data set result in missing basket prices for a given state-year combination. We replace these missing values by interpolating or extrapolating from the prices which are available for other years. We use the same procedure where the prices series for a given state exhibits implausible changes between years, using a cutoff of a 50% increase in the basket price from one year to the next.

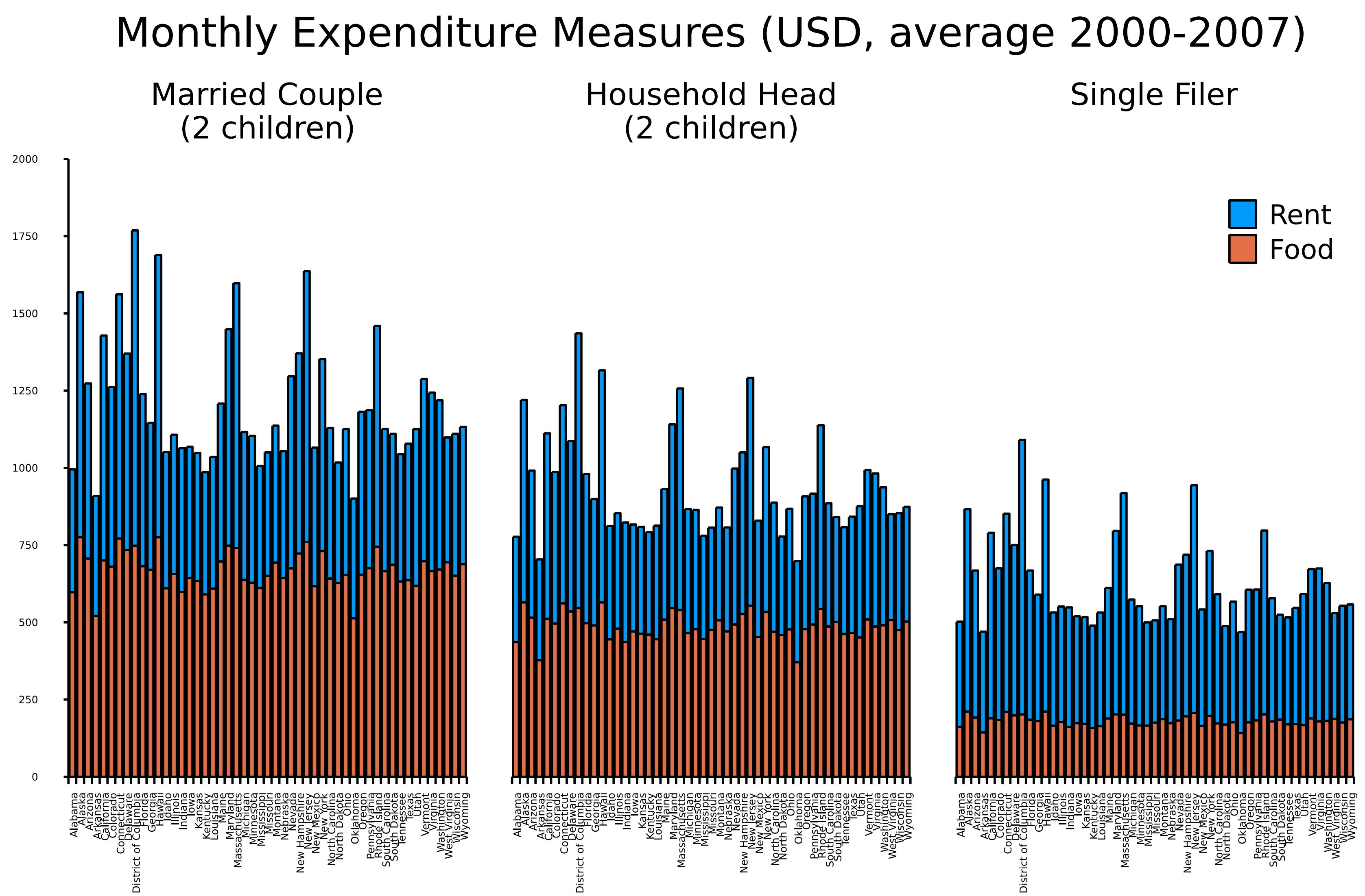

Figure 35: *Monthly subsistence expenditures (food and rent) in current USD*

G State Income Distributions

In this section, we describe how we approximate the lower tail of each state's income distribution which we use as the main input for our imputation exercise. We use data from the American Community Survey (ACS) and the Earner Study of the Current Population Survey (CPS) provided by the Integrated Public Use Microdata Series (IPUMS), covering the period 2000-2007. It is important to note that for a given state, the population of interest is the set of households which meet the specification of our prototype households, not every household (or individual) in the state.

We implement an approximation procedure as we face the challenge that neither the ACS nor the CPS are designed to be representative with respect to the population of our interest. In fact, the number of observations resembling our three prototype households is small in some states and years. Thus, it is questionable that earnings distributions constructed from these sources are robust and accurate descriptions of our population of interest. We address this challenge by fitting a (truncated) lognormal distribution to the data for each state. The lognormal distribution is known to fit income distributions well so we rely on this functional form to characterize the lowest tail.

Specifically, for every state and year, we obtain median and mean incomes of our three prototype household from the ACS. Household labor income is calculated as the sum of the incomes of the working age individuals in the household. During this exercise, we relax the requirement on the ages of children and include households containing two children who are both under 18. We report summary statistics for the household head of each of the household prototypes in tables 9 to 12 at the end of this section as these characteristics play an important role in determining the respective income distributions. Finally, we truncate the distributions at the 90th percentile to allow for the fact that the upper tail may have a different distribution.[53]

Next, we use the fact that identifying the two parameters of a lognormal distribution can be achieved from

$$\text{Median} = \exp(\mu) \tag{28}$$

$$\text{Mean} = \exp(\mu + \sigma^2/2) \tag{29}$$

Thus, for every state s and year t, we obtain the parameters of the lognormal distribution from the corresponding income distribution $Y_{s,t,i}$ (where i denotes the household type) as follows

$$\hat{\mu}_{s,t} = \ln\big(\text{median}(Y_{s,t,i})\big) \tag{30}$$

$$\hat{\sigma}_{s,t,i} = \sqrt{2\big(\ln(\text{mean}(Y_{s,t,i})) - \hat{\mu}_{s,t}\big)} \tag{31}$$

Next, to construct a state, year and type specific support from above for the lognormal distributions, we use income data from Sommeiller and Price (2014). This paper estimates the distribution of top *tax units* and so it is likely that the value we use represents an individual

[53]Evidence for this phenomenon is presented by, for example, Atkinson, Piketty, and Saez (2011).

or a household which does not meet the specification of our prototype household. Hence, as a robustness check, we also compute the percentiles using maximum incomes from the ACS. The results are unaffected.

We carefully construct a measure for the lower bound for the approximated distributions as their lower tail is our main object of interest. To account for state minimum wages, we obtain the empirical distributions of hourly wages in each state from the CPS Earner Study. We pool adjacent years to minimize concerns regarding small sample sizes. Figure 36 plots the mean of the first two percentiles of each state's wage distribution. There is a positive time trend as these lowest wages are generally larger for later years. However, the cross-state discrepancies are considerable; they are larger than the time variation.[54]

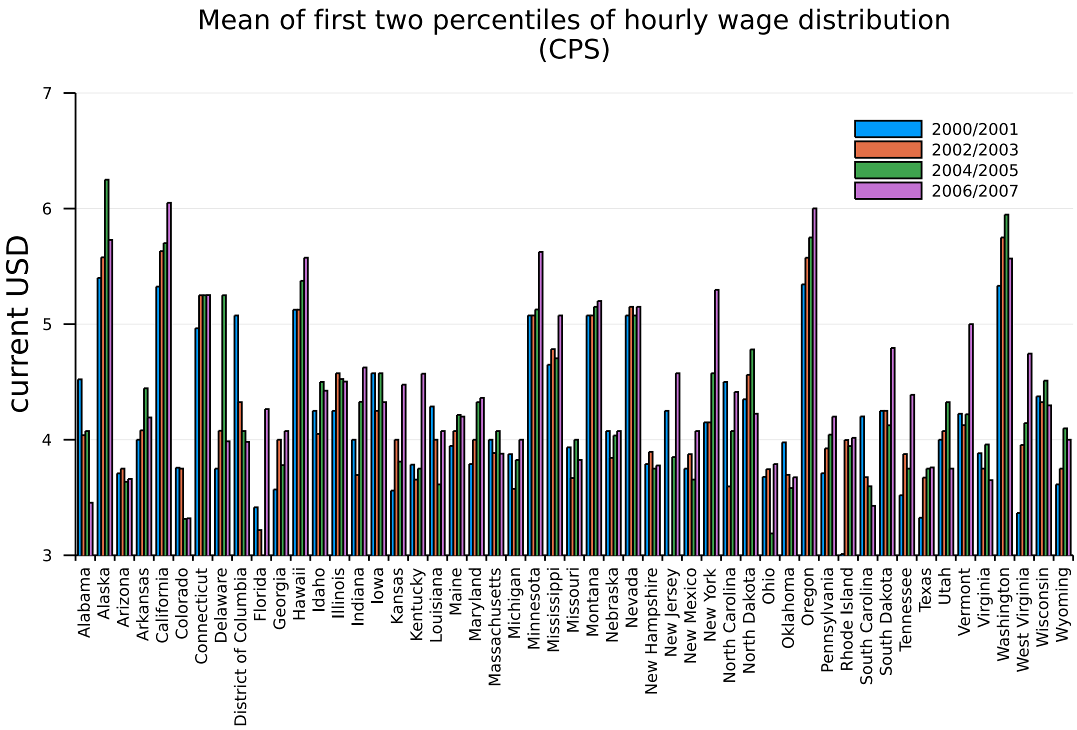

Figure 36: *Lowest hourly wages by state and year pairs. Source: CPS Earner Study*

Moreover, using this measure as a lower bound captures differences in the bottom of each state's income distribution which are driven by state specific minimum wage regulation; figure 37 shows that states with higher than federal minimum wages have higher wages at the lower end of their distributions.

[54]Some of the time differences are driven by changes of state minimum wages. For example, New York's minimum wage increased from 5.15 in 2004 to 6.75 in 2007.

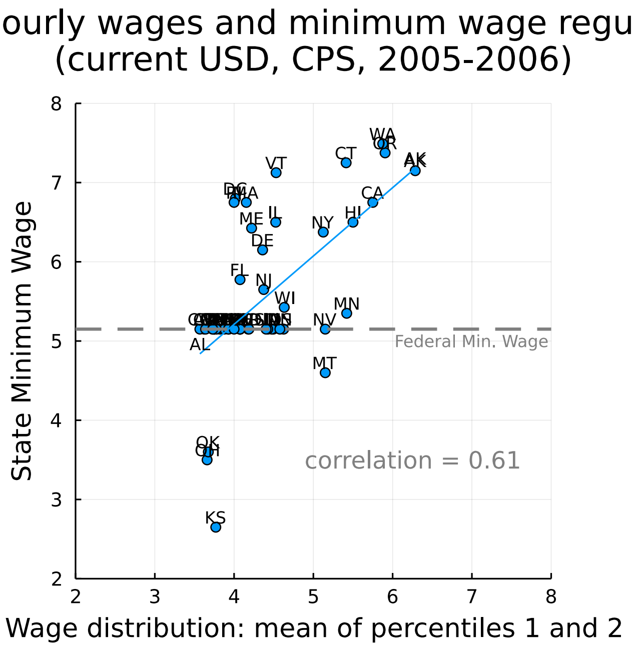

Figure 37: *Relationship between minimum wages and lowest hourly wages. Source: CPS Earner Study*

Finally, we assume that both spouses of the Miller prototype household work at least half time, i.e. the household supplies a total of 52*5*4*2 = 2080 hours per year. For the household head and single filer households, this number is 1040. Multiplying these values with the lowest wages of each state shown in figure 36 provides the lower bound we apply to the lognormal distributions.

Armed with these specifications, we draw one mio observations from each state's lognormal distribution and truncate the distributions using the lower and upper bound values. From the resulting distributions, we select the first 20 percentiles. We illustrate the results of our procedure in table 8 which shows the first and 20th percentile values as well as the means of each state income distribution for 2005 for all three prototype households.

State	Married Couple			Household Head			Single Filer		
	mean	*p1*	*p20*	*mean*	*p1*	*p20*	*mean*	*p1*	*p20*
Alabama	25146	14323	32270	7316	4663	9581	10527	5704	14115
Alaska	34416	21824	42312	13539	7941	17691	13012	7682	17136
Arizona	28756	15933	37310	14597	8130	19015	13805	7233	18429
Arkansas	24092	14231	30457	8247	5194	10710	9265	5410	12325
California	29443	15773	38629	12128	6947	16296	16596	8925	22090
Colorado	32462	18787	41401	11480	5693	15735	13664	7195	18196
Connecticut	28934	14441	38905	12386	6817	16673	15524	8307	20672
Delaware	35014	20960	43979	10302	6137	13872	14018	7756	18508
District of Columbia	29212	13946	39680	9513	5260	12840	15571	7591	21429
Florida	26231	14311	34188	10107	5079	13769	11962	5937	16320
Georgia	26862	14638	34991	10232	5537	13656	11966	6083	16275
Hawaii	34415	21339	42671	9559	6208	12258	12470	6974	16688
Idaho	25360	15543	31692	10181	6039	13150	10715	6092	14104
Illinois	27423	14495	36160	10107	5642	13662	13542	7158	18160
Indiana	29686	18091	37061	11516	6852	14677	12597	7163	16331
Iowa	28141	17154	35164	12823	7691	16253	11939	7261	15060
Kansas	26738	15401	34166	11149	6039	14782	11239	6307	14669
Kentucky	26212	15364	33216	11007	6282	14243	10930	5914	14510
Louisiana	27174	16240	34125	7270	4278	9783	9547	5034	12972
Maine	28555	17660	35460	9942	5576	13207	10700	6073	13993
Maryland	40037	23417	50718	15655	8425	20698	18776	10505	24395
Massachusetts	33069	17964	43200	10568	5539	14455	14932	7815	20008
Michigan	31035	18501	39110	10898	5862	14509	14340	8137	18540
Minnesota	30548	17553	39075	13461	7618	17584	14328	8380	18376
Mississippi	23005	13259	29325	8548	5490	10962	9520	5680	12564
Missouri	24824	13907	32027	9675	5411	12823	10931	5954	14506
Montana	25069	15188	31415	12651	10134	14101	9033	5869	11710
Nebraska	30576	19560	37457	8989	5045	12104	11219	6378	14580
Nevada	25431	13852	33221	11710	6432	15895	13374	7126	18031
New Hampshire	40004	25462	49143	11157	6034	14809	14538	8264	18759
New Jersey	34887	19169	45244	12352	6341	16742	16769	8604	22507
New Mexico	27426	16578	34342	7581	4343	10350	10519	5468	14239
New York	24541	12177	33128	9975	5606	13555	13474	6854	18432
North Carolina	24325	13101	31890	9453	5329	12596	10085	5436	13673
North Dakota	29983	19439	36577	11074	6548	14262	9268	5723	12028
Ohio	28010	16396	35485	10245	5351	13739	13136	7332	17079
Oklahoma	21851	11942	28497	7626	4348	10307	10181	5526	13491
Oregon	23155	12382	30473	12307	7282	16053	13123	7729	17000
Pennsylvania	27753	15784	35586	9266	5131	12545	11608	6264	15442
Rhode Island	32847	19362	41536	10570	5672	14175	12837	6767	17162
South Carolina	24938	13935	32144	8363	4636	11232	11338	6245	14913
South Dakota	30867	20338	37409	7607	4744	10071	9583	5628	12387
Tennessee	22731	12333	29701	9601	5320	12689	10200	5374	13781
Texas	24158	12727	31934	8888	4802	12160	12526	6496	16842
Utah	26335	15546	33367	15508	9825	19164	13141	7397	17103
Vermont	24663	13724	31908	13400	7797	17173	9456	5363	12602
Virginia	31737	17338	41366	11757	6155	15851	13417	6784	18235
Washington	31110	17852	39821	12712	7491	16632	15542	8889	20174
West Virginia	23357	13824	29534	7983	4865	10531	9294	5266	12385
Wisconsin	34584	22240	42233	15751	10152	19350	13644	8084	17358
Wyoming	28966	17496	36332	7749	4705	10479	12526	7158	16186

Table 8: *Approximated income distributions for working poor prototype households (2005, in USD)*

Prototype Families: Summary Statistics Tables 9 to 12 show summary statistics of the state and year sample of each prototype family from the ACS. These are the samples which we use to compute the moments of the state (and household type) specific income distributions. The statistics refer to the head of the household.

	Miller	Jones	Single
2000	38.5	36.6	56.2
2001	38.6	36.9	57.0
2002	38.8	37.1	57.2
2003	39.1	37.3	57.4
2004	39.3	37.5	57.5
2005	39.5	37.6	58.0
2006	39.6	37.7	55.0
2007	39.6	37.8	55.2

Table 9: *Average age in years*

	Miller	Jones	Single
2000	28	86	60
2001	30	85	60
2002	30	85	60
2003	31	85	60
2004	31	84	60
2005	30	85	59
2006	31	85	55
2007	33	85	55

Table 10: *Percentage female*

	Miller	Jones	Single
2000	7.8	6.8	7.0
2001	7.8	6.9	6.9
2002	7.9	6.9	7.0
2003	7.9	7.0	7.0
2004	8.0	7.0	7.1
2005	7.9	7.0	7.0
2006	8.0	7.0	6.8
2007	8.1	7.1	6.8

Table 11: *Educational attainment measured as the average number associated with the eleven educational categories reported in the ACS. The range of values in the table summarize: 6 - 12th grade, 7 - One year of college, 8 - Two years of college, 9 - Three years of college*

Race				
Miller				
	White	Black	Asian	Other
2000	87.2	4.8	3.8	4.2
2001	86.6	4.6	4.0	4.8
2002	85.8	4.7	4.3	5.3
2003	85.9	4.8	4.3	5.1
2004	85.9	4.6	4.7	4.9
2005	84.2	4.8	5.0	6.0
2006	83.8	5.0	5.1	6.1
2007	83.5	4.8	5.5	6.2
Jones				
	White	Black	Asian	Other
2000	69.0	22.4	1.8	6.8
2001	68.7	22.1	1.9	7.3
2002	69.7	21.6	1.7	7.1
2003	68.6	21.8	2.0	7.6
2004	68.6	22.0	1.8	7.6
2005	66.3	23.1	1.9	8.7
2006	66.0	23.0	1.9	9.1
2007	65.8	23.1	2.0	9.0
Single Filer				
	White	Black	Asian	Other
2000	84.8	9.9	2.3	3.0
2001	84.8	9.7	2.2	3.3
2002	84.5	9.7	2.3	3.5
2003	84.4	10.1	2.4	3.1
2004	84.5	9.8	2.5	3.2
2005	83.4	10.6	2.4	3.6
2006	79.3	13.4	2.5	4.8
2007	78.9	13.7	2.6	4.8

Table 12: *Race (in %)*

H Additional Results

H.1 Including Medicaid

The Medicaid calculator of Hoynes and Luttmer (2011) does not include Washington DC. Hence, we are imputing zero Medicaid transfers but keep DC in the graphs for consistency.

Dispersion of Disposable incomes

Figures 38 to 40 show the dispersion of disposable incomes when we include the Medicaid and CHIP transfer program in our imputations.

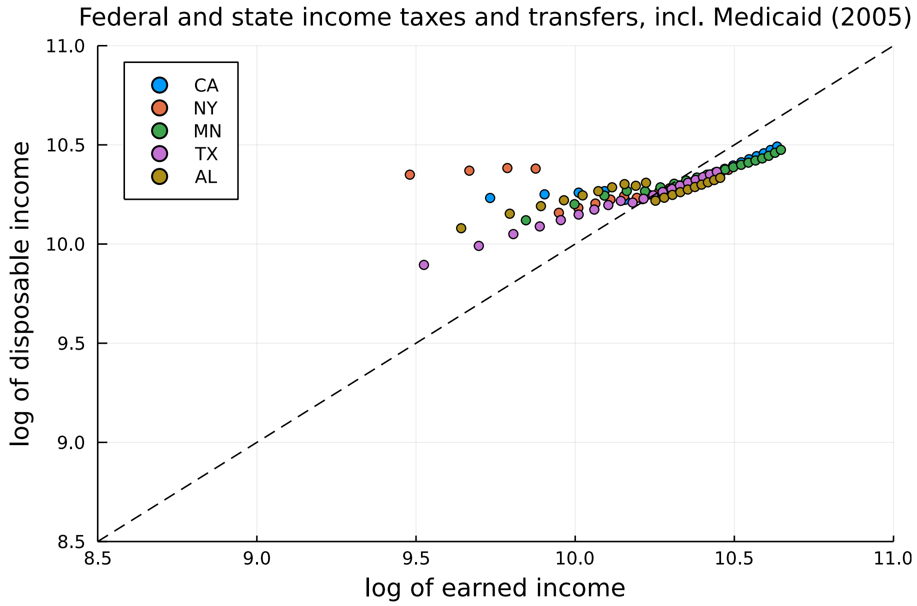

Figure 38: *Miller Family - Income Taxes and Transfers, including Medicaid*

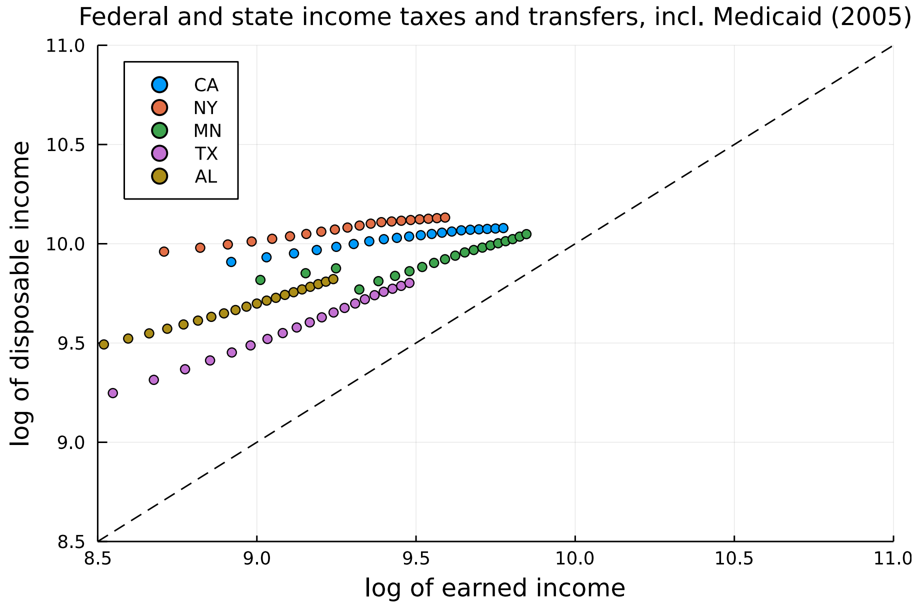

Figure 39: *Jones Family - Income Taxes and Transfers, including Medicaid*

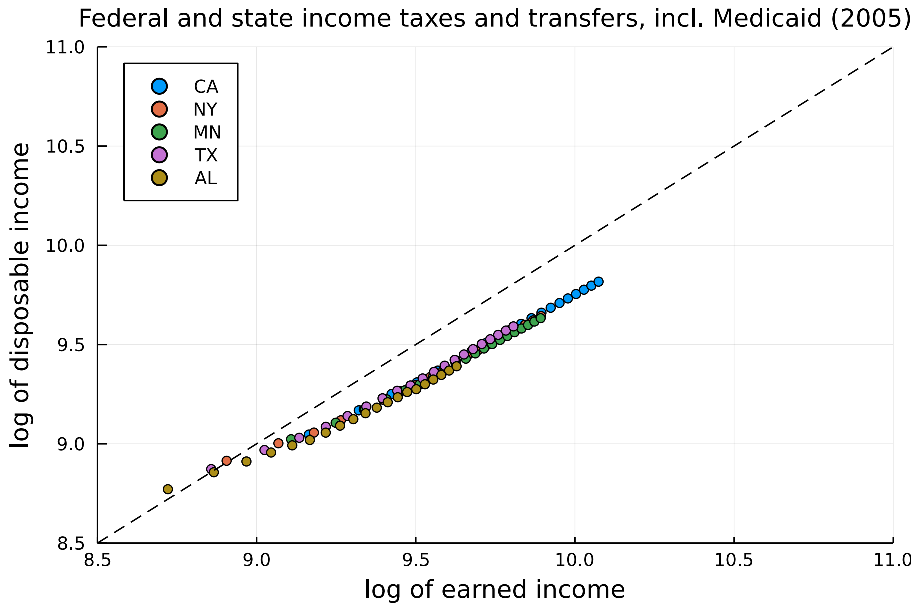

Figure 40: *Single Filer - Income Taxes and Transfers, including Medicaid*

Insurance against Earnings Loss

The following results refer to the Miller family.

Federal Perspective

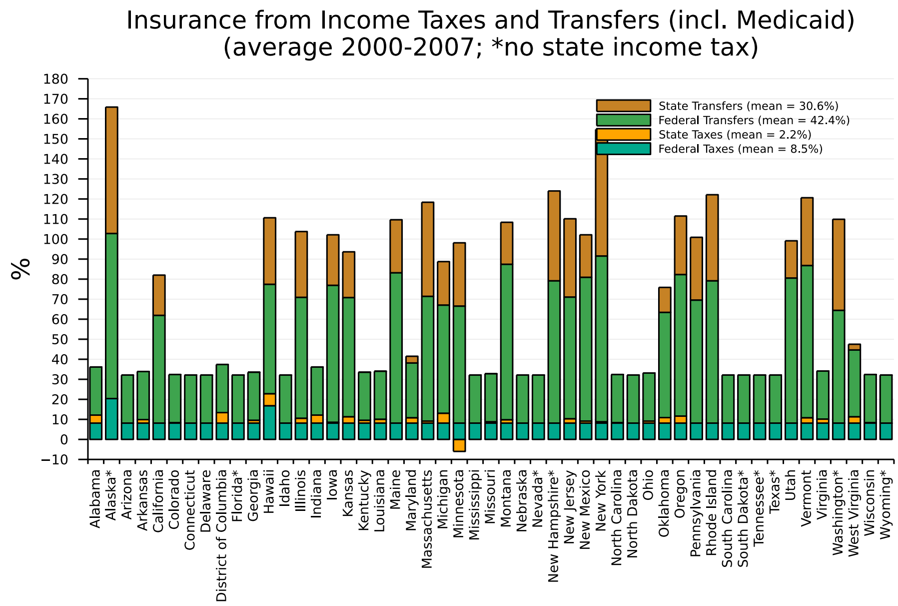

Figure 41: *Miller Family - starting from FPL (nominal terms)*

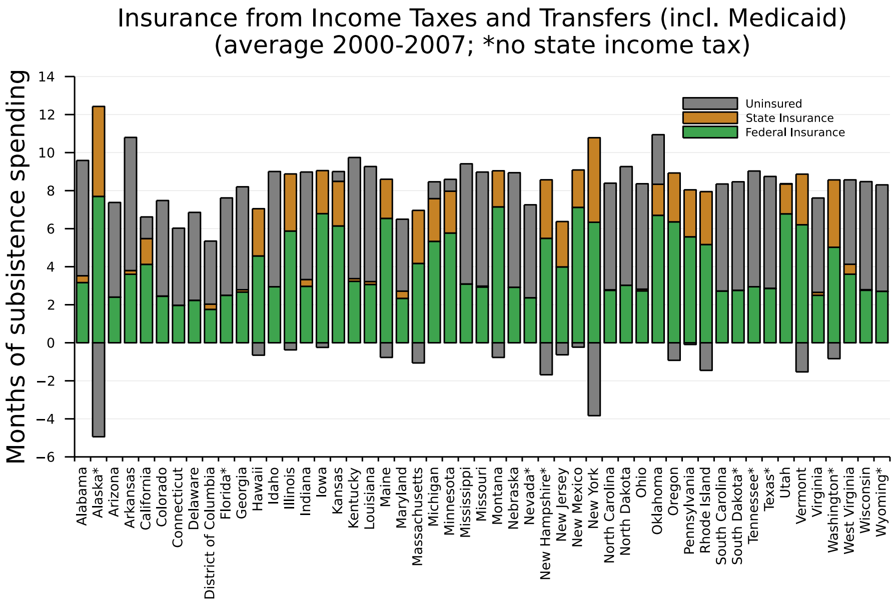

Figure 42: *Miller Family - starting from FPL (real terms)*

State Perspective

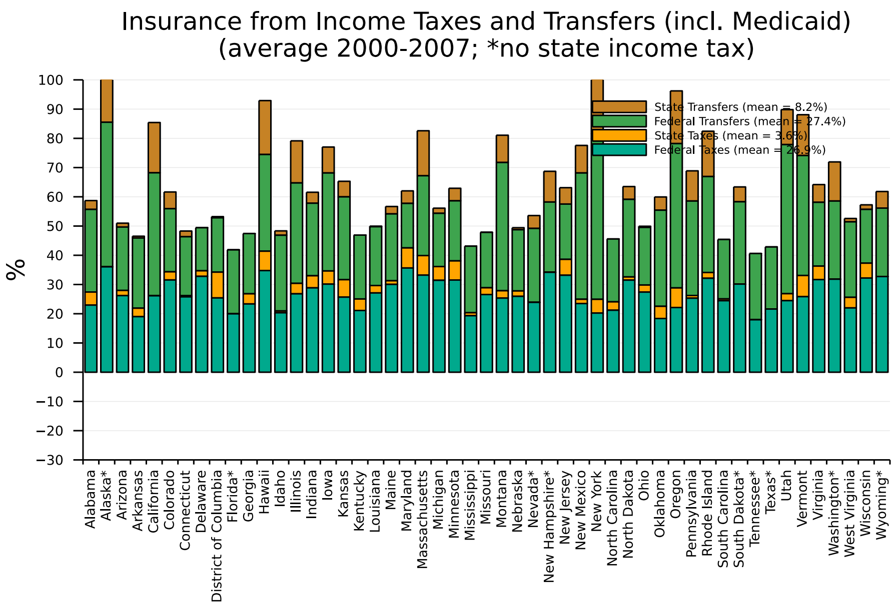

Figure 43: *Miller Family - first 20 percentiles (nominal terms)*

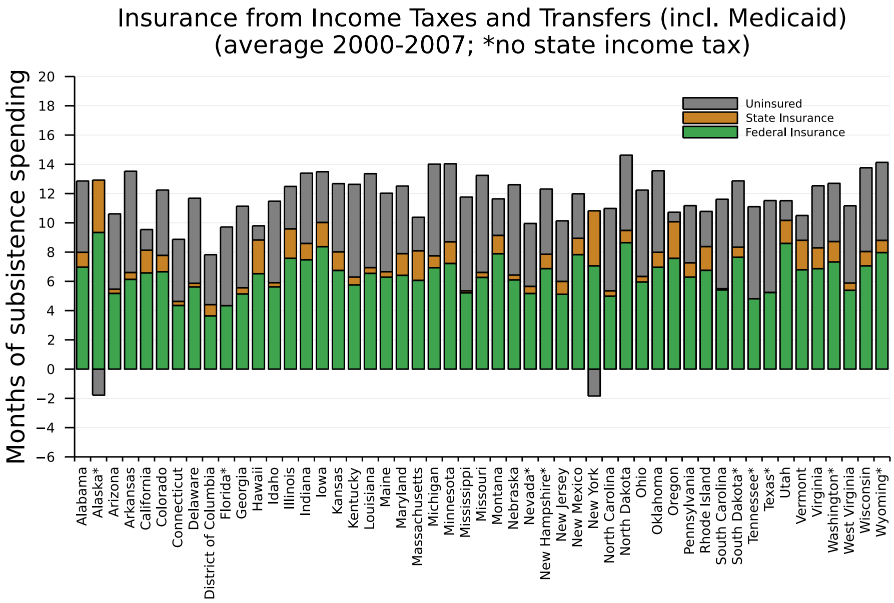

Figure 44: *Miller Family - first 20 percentiles (real terms)*

H.2 Lower Shock Duration

In this section, we present the results of our analysis in which we reduce the duration of the earnings shock. This adjustments is identical to assuming a smaller shock size as, for tax filing purposes, a large shock lasting for a short time has the same effect as a small shock lasting for a long time – as long as they imply the same total reduction in earnings. We reduce its duration from one year to one month so its corresponding size is 50%/12 = 4.2% ≈ 4%. The following results refer to the Miller family.

State Perspective

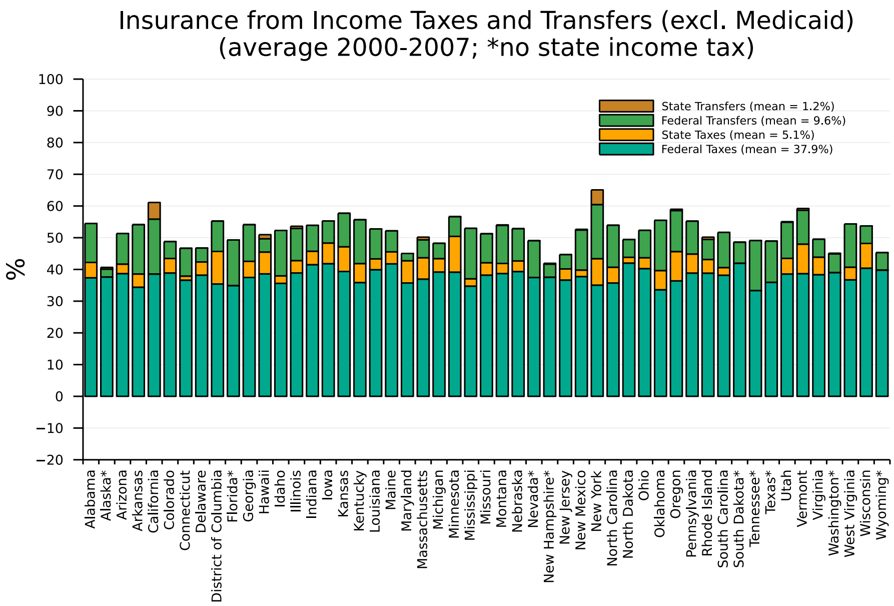

Figure 45: *Miller Family - first 20 percentiles (nominal terms)*

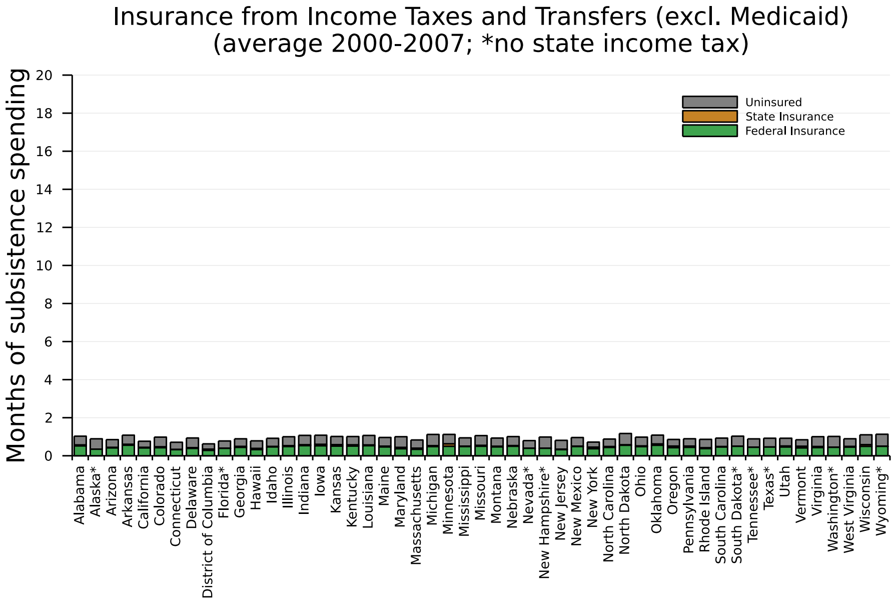

Figure 46: *Miller Family - first 20 percentiles (real terms)*

I Income Insurance and State Characteristics

I.1 Data Sources

We use data from the 2000 and 2020 Censuses to compute the share of urban and black population for each state. For the political leaning, we use data from Altig et al. (2020) which classify states into Republication, Democrat or Swing using the share of votes given to presidential candidates. We recode this information into a binary indicator (Democrat or else). To compute means of the state earned income distribution and its Gini coefficient, we use data from the ACS.

I.2 Regression Results for the Single Filer

Note: As the Single Filer does not qualify for Medicaid participation, we only report results for the baseline case.

	Nominal (χ)	Real (baskets)
	(1)	(2)
Constant	3.212	0.758
	(6.296)	(0.701)
Price Level	0.004	-0.000
	(0.003)	(0.000)
Democrat (0/1)	0.564	0.067
	(0.603)	(0.067)
Has Income Tax	3.178***	0.357***
	(0.592)	(0.066)
Gini Coefficient	-12.916	-2.154
	(14.588)	(1.624)
Mean Income	-0.047	0.000
	(0.046)	(0.005)
Share Urban Population	3.333	0.343
	(2.070)	(0.230)
Share Black Population	0.028	0.003
	(0.026)	(0.003)
Estimator	OLS	OLS
N	51	51
R^2	0.522	0.509

Table 13: *Single Filer - Investigation of baseline results*