Public Insurance in Heterogeneous Fiscal Federations: Evidence from American Households

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Abstract

The literature on fiscal federalism usually argues that policies involving income reallocation should be administered by the highest level of government. This argument, however, neglects a uniformity constraint, which limits regional variation in its tax and welfare policies. Our paper explores the extent to which income support for poor households varies across US states due to the interaction between the federal government's uniformity constraint and regional variations in local economic conditions and the net transfer policies of state governments. Our results are based on a simulation of the combined response of federal and state net transfers to a pre-tax earnings shock. They point to large differences in the level of insurance against income shocks experienced by households with low incomes in different states.

Keywords: Fiscal Federalism, Insurance, Regional Policies, Microsimulation

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1 Introduction

Which level of government should be responsible to design and implement policies providing income support to poor households? The overall majority of economists studying this question argue that it should be the highest level, i.e. the central or federal government. Their main argument is that tax base mobility and regional variation in fiscal capacity preclude lower levels of government from implementing such policies successfully[1]. However, the highest governmental level typically suffers from a regional uniformity constraint; because of equity considerations, federal governments have to treat citizens residing in different regions of the country alike and typically only condition their social policies on variation in nominal income and household demographics. While this limitation is an important pillar of a country's cohesion, it can have unintended implications for the efficacy of federal policies when regions are very heterogenous. This is particularly true for policies designed to insure households against economic hardship by providing a social safety net.

In his classic work 'Democracy in America', Alexis de Tocqueville characterizes the implications of this uniformity constraint 'a great cause of trouble and misery' in unitary nations such as his native France. Regarding the United States of America, however, he was confident that due to her federal character, her citizens would not suffer the consequences of this specific policy restriction. Yet, in recent years, given increasing economic inequality with a pronounced geographic element, the interaction of a uniform federal tax and transfer schedule and regional variation in incomes, price levels and state policies receives more and more attention by US policy makers and scientists.

Academic proposals aiming to alleviate the adverse effects of the uniformity constraint usually belong to one of two types: price indexation of federal policies and placed based policies. An example for the former are Bronchetti et al. (2017). They find that geographical variation in food prices causes severe regional differences in the real value of the federal Supplemental Nutrition Assistance Program (SNAP) benefits, which are fixed in nominal terms nationwide. Their suggestion is to reform SNAP and to index its benefits to a regional price indicator. Regarding placed based policies, Austin et al. (2018) argue that domestic migration alone can no longer dry out pockets of unemployment and poverty. They advocate for federal employment subsidizes to regions with high non-working rates, explicitly suggesting targeted, non-uniform federal policies.

In this paper, we re-examine empirically the effect of the given division of fiscal responsibilities in the US federal system on income support for poor households. We put particular emphasis on regional economic heterogeneity and our examination recognizes and accounts for two sources of regional variation in the US which may interact in undesirable ways with the federal government's uniformity constraint:

1. **Differences in economic conditions** There are large and persistent variations in price levels and income distributions between US states. In other words, the purchasing power of one US Dollar varies not only over time but also across states. This variation is illustrated in more detail in Section 2.

[1] In contrast, lower levels of government are considered to have better information on preferences of local residents regarding public goods. For this reason it is generally recommended that local governments play an active role in their provision.

2. **State policy autonomy** US state governments have considerable autonomy in choosing their own budgetary policies which is reflected in both taxes and transfers to households. Section 2 provides more details on respective differences.

In order to elicit the impact of the interaction of 1. and 2. with the federal government's uniformity constraint on income support for households, we consider how the disposable income of a prototype household responds to changes in pre-tax labour earnings, and how this response changes with location. To this end, our microsimulation includes the main US means tested welfare programmes as well as income taxes and tax credits administered at the state and federal levels. In addition, we adjust our results for local living costs, allowing us to measure the impact of the regional variation in price levels and to express the changes in disposable income in comparable household consumption units. Furthermore, our simulation approach allows to separate the contributions of federal policies and state policies, and compare households with the same real income living in different states.

For the purpose of our simulation we abstract from the possibility of job loss and focus on fluctuations of disposable income due to earnings risk. There is ample evidence on the importance of household earnings risk, which can result from self-employment, shocks to productivity or performance-related bonus pay. To illustrate the ubiquity of this kind of risk, we refer to results shown in Storesletten et al. (2004) who report that for an average worker in the US, the annual standard deviation of these shocks amounts to 11,500 in 2004 US-Dollars. Daly and Valletta (2008) provide similar evidence for Germany, Great Britain and the USA.

A natural question to answer within this framework is whether the pattern of state policies mitigates the distortions caused by the uniformity of federal policies. In other words, we might expect that the redistribution motive within states would push towards more uniform support for the poor across the entire country. In addition, federal grants to state governments are designed to mitigate differences in fiscal resources; Medicaid grants to states, for instance, are more generous for poor states than they are for rich states[2]. Yet, our findings suggest that this conjecture is incorrect; we find that an earnings shock to a poor household triggers a much weaker net transfer response if the household is located in Mississippi, a poor state, than if it is located in Massachusetts, a rich state.

Related Literature The question which level of government should be assigned what kind of responsibilities is known as the *assignment problem* in the literature on fiscal federalism. Under the assumption of a benevolent social planner, the so called 'first generation' fiscal federalism (FGFF) provided the normative insight that policies involving income reallocation are best implemented by higher levels of government. Prominent examples of this view are Oates (1999), Ladd and Doolittle (1982), Inman and Rubinfeld (1996) as well as Boadway and Tremblay (2012). A more recent strand of the fiscal federalism literature, called 'second generation' fiscal federalism (SGFF) has challenged a fundamental assumption of these papers which is that subnational policy makers can be considered altruistic agents of the federal government. SGFF emphasizes the fact that subnational policy makers have their own fiscal and political interests, which

[2]The amount of Medicaid grants to states is determined by the federal medical assistance percentage (FMAP) which stipulates the percentage of a dollar of state spending on Medicaid which will be matched by the federal government. FMAP rates are a function of state per capita income relative to the US average, and vary from a legislated floor of 50% to a maximum of 83%

may differ from those of benevolent federal planners (Oates, 2005; Weingast, 2009). As it has been widely documented that US state governments engage in considerable income reallocation (Moffitt, 2016; Baicker et al., 2010; Gordon and Cullen, 2012) – which contradicts the normative conclusions of FGFF – our model captures variation in state policies and its interaction with the uniform federal tax and transfer schedule in great detail.

Albouy (2009) corroborates our emphasis on the federal uniformity constraint and provides numerical estimates for the shadow cost of the uniform income tax schedule. This paper observes that since US federal income taxes are based on nominal income, workers with the same real income pay higher taxes in high-cost areas than in low-cost areas. An empirical simulation suggests that the resulting incentives to relocate to low-cost areas have considerably lowered employment, house prices and land values in high cost areas in the long run. Conversely, Albouy (2012) finds that fiscal equalization payments to Canadian provinces, which aim to overcome differences in tax bases, impose inefficiency costs of 0.41% of income. In particular, equalization payments skew benefits towards less productive and less amenable provinces, and discourage workers from living in highly productive areas where wages are high.

There are also some papers which attempt to evaluate spatial distortions caused by the uniformity of federal taxes and transfers to households. Kaplow (1995) asks whether adjustments to the US Federal tax system to account for regional cost of living differences would promote distributional objectives, and whether such adjustments would be efficient. The discussion notes that differences in local amenities (like crime or pollution) mean that using standard cost of living indices to achieve this would be misleading, and suggests comparing wages across regions for identical occupations as a basis for measuring cost of living differences. Using a formal model, Glaeser (1998) demonstrates that the optimal indexing scheme depends on the complementarity between local amenities and other consumption goods. Based on the correlations between state price levels and Aid to Families with Dependent Children (AFDC) benefits, which were set by state authorities, this paper finds a level of implicit indexing in these benefits which is probably too high to be optimal.

Our paper also relates to the literature advocating for location-based policies in the US. As mentioned earlier, Austin et al. (2018) propose targeting of pro-employment policies towards American regions with high rates of long-term unemployment and non-employment. They document the failure of convergence of living standards across regions in recent years and present evidence that the labour supply response to public interventions is greater in more distressed areas. Bronchetti et al. (2017), also mentioned earlier, propose that adjusting SNAP benefit levels to account for geographic variation in food prices might improve healthcare and school engagement for children in low-income households. Ziliak (2016) and Hoynes and Ziliak (2018) also suggest similar adjustments to the SNAP benefits formula to alleviate food insecurity.

Our household perspective complements the existing empirical literature on risk sharing and redistribution between US states which considers changes in income at the state level. For example, Von Hagen (1992) finds that the US federal fiscal system provides little insurance against shocks to state income. Asdrubali et al. (1996) decompose the sources of risk sharing between states into private and public insurance; while they find that the federal government does play a role in smoothing gross state products, much more insurance is provided by capital and credit markets. More recently, Rodden and Wibbels (2010) include the US in a panel of seven federations for which they find that central government grants contribute to rather than alleviating the pro-cyclicality of subnational government spending. We depart from this specific literature by thinking of the purpose of transfers in terms of household welfare as opposed to state budgets, and therefore conducting the empirical analysis at the household level.

The closest paper to ours is Hoynes and Luttmer (2011), which evaluates the welfare impact of state tax and transfer programs. In their paper, the welfare value of these programs is decomposed into a redistributive value, derived from the response to predictable income changes, and the insurance value, which responds to unexpected shocks. Grant et al. (2010) also contains an analysis related to our paper, finding a negative correlation between state levels of redistributive taxation and the standard deviation of the consumption distribution. Our research question is different from these papers in that we examine the possibility that state policies may be partly designed to address limitations in federal policies. In terms of methodology, our paper is related to Dolls et al. (2012). This paper compares the ability of the tax and transfer systems in the US and 19 European countries to provide income insurance against aggregate shocks to gross income and employment, using microsimulation of the automatic stabilizers in these countries. The results indicate a slightly stronger response of automatic stabilizers amongst EU countries than among US states.

The rest of the paper is organized as follows. In section 2 we clarify the available channels of income support in the US by outlining the main features of the American federal fiscal system, in particular highlighting evidence on the variation in state level resources and welfare policies. In Section 3 we describe the simulation which we perform to capture the responses of federal and state net transfer systems to changes in pre-tax income. In Section 4 we present our results. In Section 5 we consider several factors which could be driving the results. In Section 6 we offer concluding remarks.

2 The United States Federal System

In this section we provide evidence on the policy restrictions faced by federal policy makers which motivate our investigation. We do so by refering to the fiscal structure of the US as an exemplary federation. We present the basic flows between the federal budget, state budgets and households in figure 1.

Both the federal and the state governments raise revenue through taxes on income, consumption and property, although the composition of taxes varies widely. In figure 1, federal and state tax schedules – including tax credits – are illustrated by τ^f and τ^s, respectively. Note that households residing in both states face the same federal tax schedule. Welfare programs to targeted groups of households are provided through several funding systems, including:

- Direct transfers from the federal government to households financed from federal revenues (g^f)
- Direct transfers from state governments to households financed from state revenues (g^s)
- Transfer programs implemented and administered at the state level, using grants provided by the federal government (G^f). These can also include programs which use a mixture of funding sources, such as Medicaid, which is co-financed by state and federal revenues.

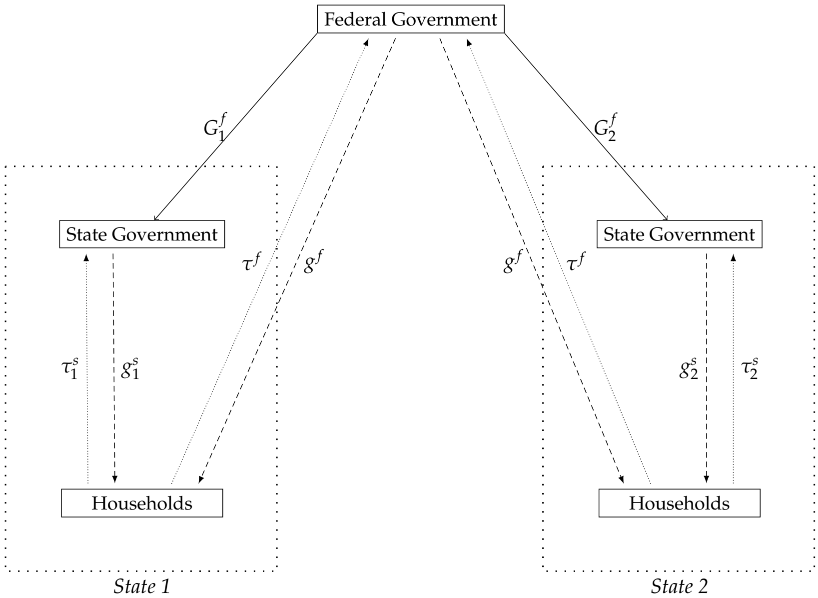

Figure 1: US fiscal flows. τ refers to taxes, g to transfers, and G to intergovernmental grants

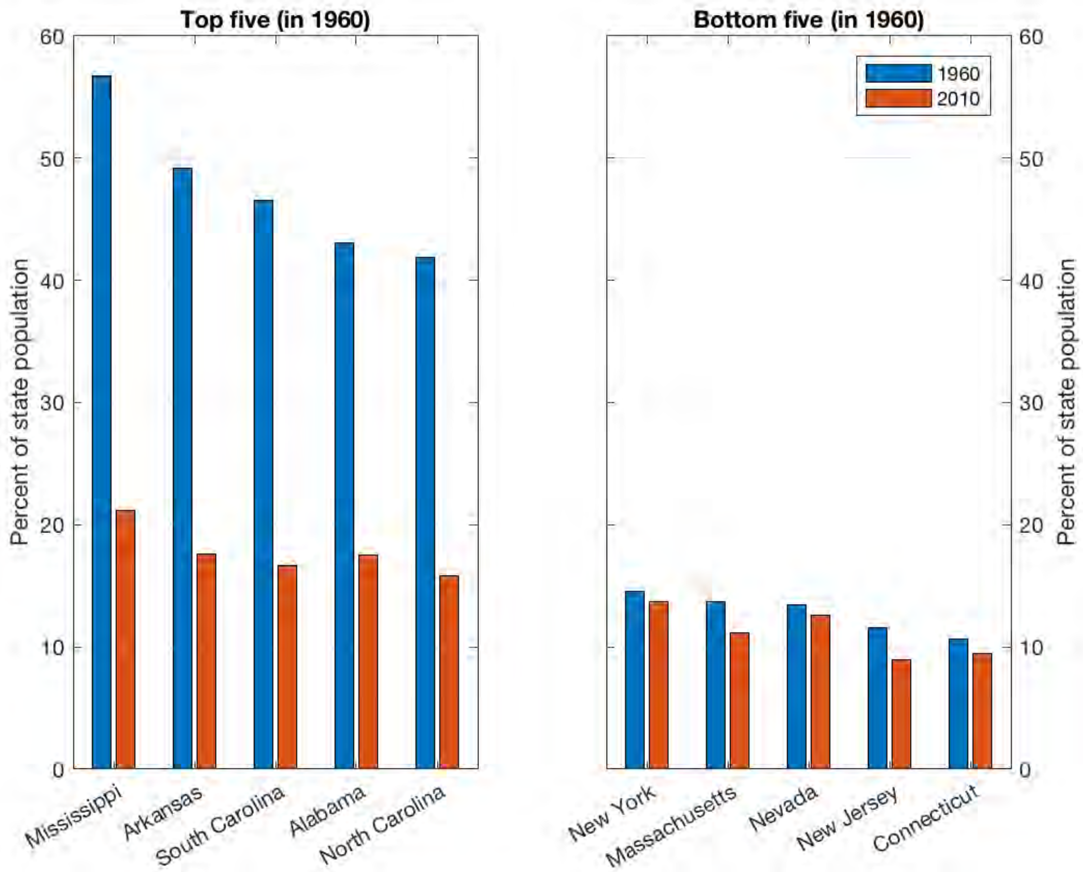

Figure 2: Percentage of families in poverty by state

Due to the uniformity constraint, the Federal government cannot condition its direct interactions with households on their state of residence. A practical implication of this restriction is that net direct transfers from the Federal government to identical households in different states will be equal in *nominal* terms. If, however, there is a welfare justification for equalizing transfers across states, it would make more sense for these transfers to be equal in *real* terms. As discussed in Ribar and Wilhelm (1999) the funding design of intergovernmental grants (matching, block, etc.) can change the effective price of spending on welfare programs. Nevertheless, as we show in the following paragraphs, the implementations of tax and transfer programs by state governments on the one hand and differences in living costs and incomes on other hand are substantial. Hence, despite targeted intergovernmental grants, it remains plausible that the combined tax and transfer system provides unequal income support across states for households with similar earnings.

Variation in Local Conditions Both the needs and the resources of the states differ because of variations in state income distributions. Figure 2 indicates the extent to which the demand for income support may vary between states, showing the proportion of households in poverty as defined by the federal poverty line in 1960 and 2010[3]; the overall incidence of (measured) poverty decreased considerably over this period, but it was still roughly twice as high in Mississippi than in a richer state like Connecticut or New Jersey in 2010. Sommeiller and Price (2014) document the variation in the prevalence of very rich taxpayers in different states; for example, the average income of the top 1% in Connecticut was \$2.2 million in Connecticut in 2011, compared with \$635K in Hawaii. Moreover, the states with relatively large populations of poor households tend to be those with fewer rich taxpayers. These distributional variations may limit the amount of redistribution which some of the states could achieve by themselves, suggesting a role for the federal government to reallocate resources *between* states.[4].

The variability of local economic conditions across states can also be seen in price levels. Figure 3 shows the states with the lowest and highest living costs as measured by regional price parities compared to the US average. We see that the price level faced by household in Hawaii is almost 20% higher than the national average, whereas that faced by a household in Mississippi and Alabama is almost 15% lower than the average. It is easy see that this introduces considerable variation in the welfare impact of federally administered policies, which tend to be fixed in nominal terms.

Variation in State Policies To illustrate the variation in state income tax systems, we compute a measure of state tax progressivity for each state. This measure reflects the income elasticity of net state collections, estimated using the constant elasticity functional form shown in Heathcote et al. (2017) to provide a good fit for net taxes at the national level. The estimates of the progressivity parameter γ for the year 2000 are shown in Figure 4. As well as state income taxes, the results also reflect the impact of deductions and state earned income tax credit systems. In general, state income tax schedules are less progressive than the federal tax, but there is large variation across states, from no income taxation (e.g. Texas), to uniform taxation (e.g. Tennessee)

[3]The Federal Poverty Line is a benchmark household income level used by the US government to determine eligibility for federal aid. It does not vary between states except for Alaska and Hawaii, which are assigned higher levels than the contiguous states and the District of Columbia.

[4]In addition, the overall majority of states have self-imposed balanced budget rules which provide legislative restrictions on the accumulation of debt.

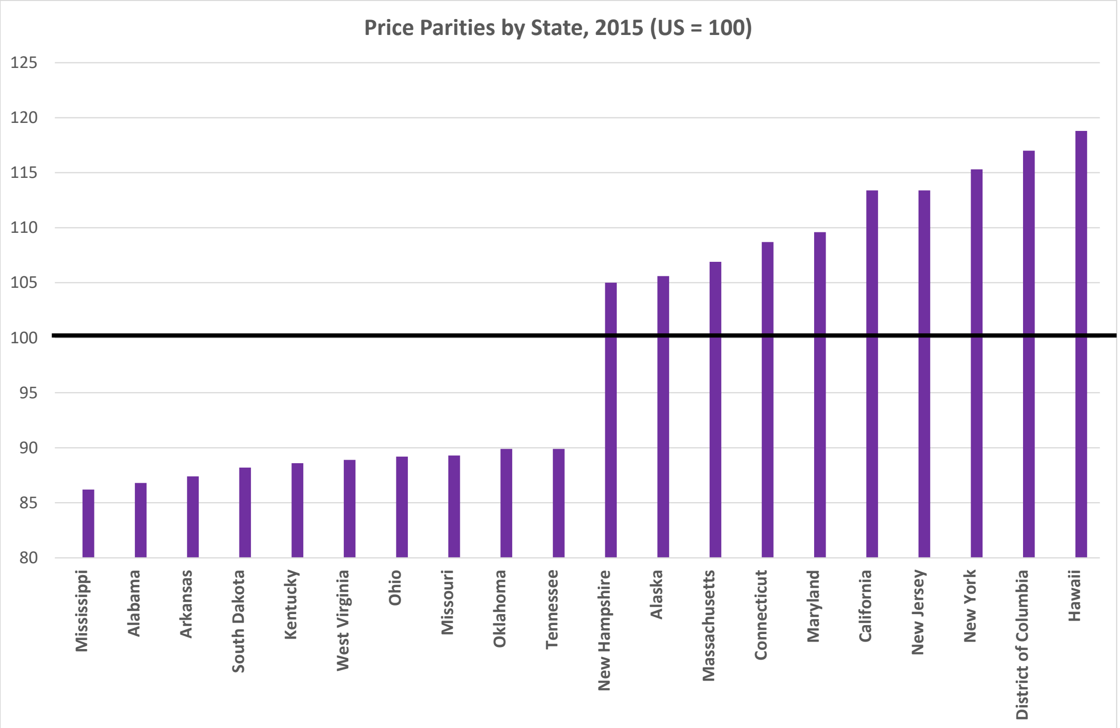

Figure 3: Regional Pricing Parities by state 2015, 10 highest and 10 lowest

to more progressive systems where, for example, New York and California have a special top rate for millionaires. Regarding the income taxation of households which are considered poor Oliff et al. (2012) document that working poor families pay state income taxes in several states while a few - Alabama, Georgia, Illinois, Montana and Ohio – even levy taxes on two parent families of four earning less than 75% of the federal poverty line.

We also see considerable differences across states in the provision of welfare programs. These differences are reflected best by programs for which the federal government provides part of the funding to states and specifies some minimal policy objectives but where states are given autonomy in the implementation details. This allows the state governments to determine which services are provided, the eligibility requirements and the generosity of provision to recipients. Figure 5 shows the percentage of the population of each state receiving Temporary Assistance to Needy Families (TANF) funds, which provide cash assistance and work incentives to low income families, and the maximum monthly benefit. Figure 6 shows the recipient percentage and average monthly benefit for Medicaid[5]. In the case of Medicaid, even states which have similar proportions of recipients, such as Kentucky and New York, have widely differing benefit levels. It is also striking, however, that the availability of benefits does not seem to mirror the indicators of need – California, for example, has one of the most expansive implementations of

[5]We should note here that the Medicaid benefits are in kind in the form of medical services rather than direct cash benefits. We provide equivalent cash values here.

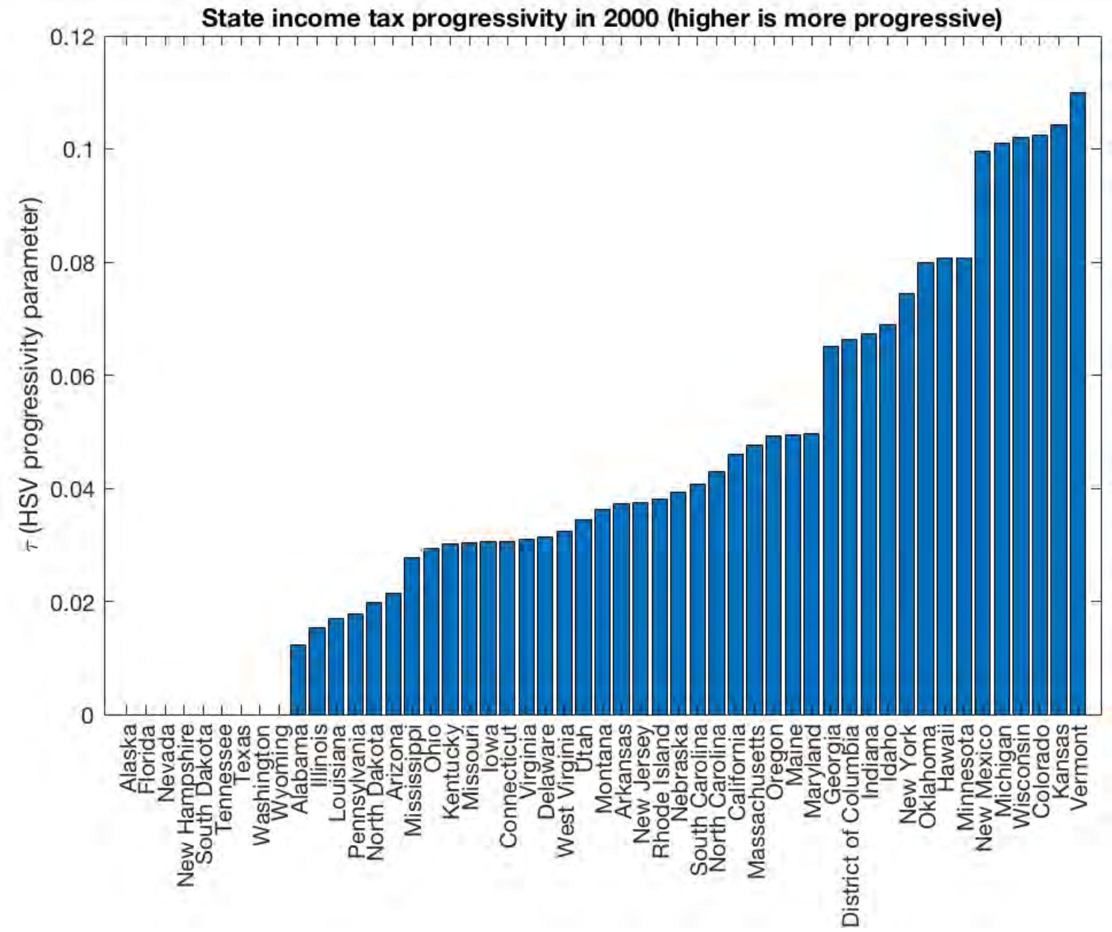

Figure 4: State tax progressivity parameters γ for HSV tax function $T(y) = y - \lambda y^{(1-\gamma)}$. $\gamma = 0$ can indicate either uniform or zero income taxation.

TANF despite having one of the lowest proportions of poor households.

While in the rest of this paper, we focus on taxes levied on earnings, states also differ in the composition of their revenue sources. In 2013, the states which drew the highest proportion of their total revenues from taxes on individual income were California, Connecticut and New York with 21%, 19% and 19% respectively[6]. However, state and local governments also draw significant revenues from taxes on corporations, property taxes and sales taxes as well as charges for licenses and financial transactions taxes. In 2013, some states relied much more on property taxes, with New Hampshire generating 36% of its revenue from this source and Texas 22%. Nevada and Washington, in contrast, are heavily dependent on sales taxes, which provide 34% and 32% of their revenues respectively. These alternative funding sources may determine the flexibility which different states have to use income tax schedules to achieve distributional goals.

[6]State & Local Government Finance Data Query System. http://slfdqs.taxpolicycenter.org/pages.cfm. The Urban Institute-Brookings Institution Tax Policy Center. Data from U.S. Census Bureau, Annual Survey of State and Local Government Finances, Government Finances, Volume 4, and Census of Governments (2013). These figures also include the revenue of local governments.

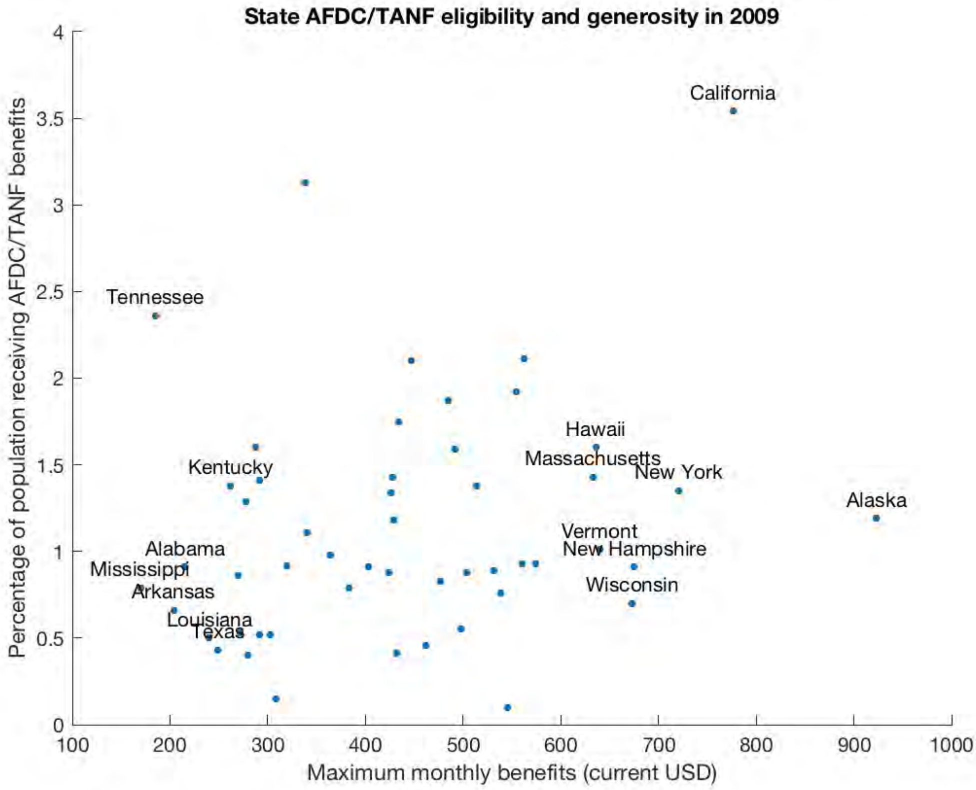

Figure 5: TANF Recipient density and benefit generosity by state in 2009

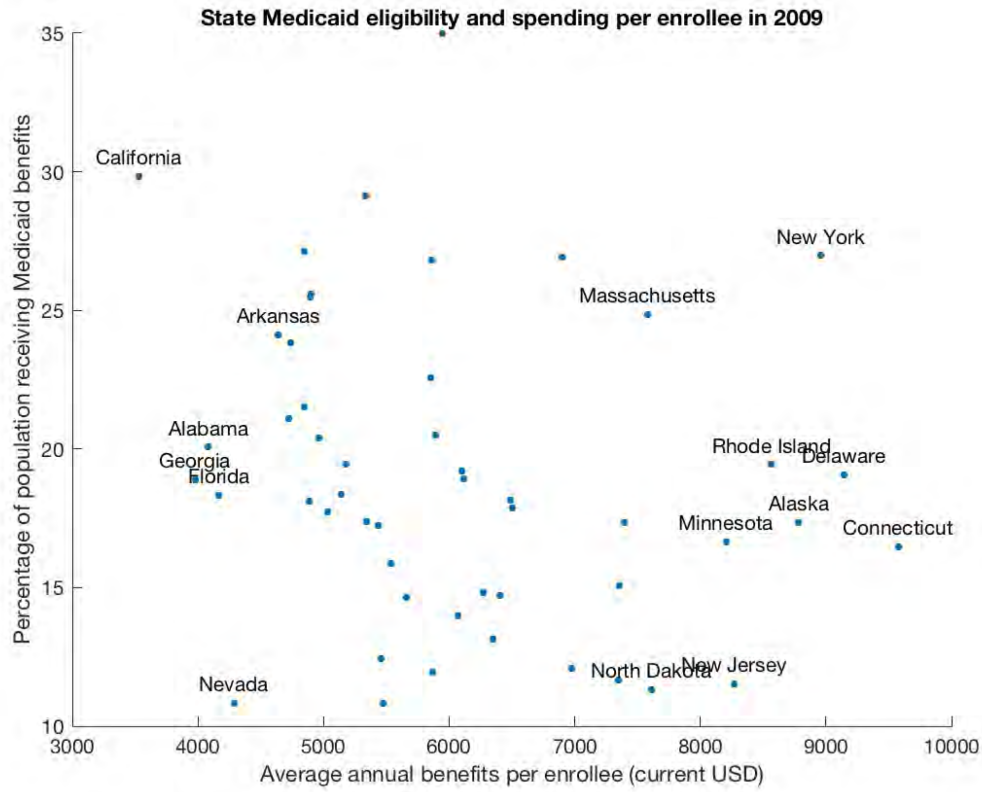

Figure 6: Medicaid Recipient density and benefit generosity by state in 2009

3 Simulation exercise

The basic idea of our simulations can be summarized as follows. For a given year, we place a prototype household in each US state with a given level of pre-tax earnings. We then shock this pre-tax income and calculate the change in ***disposable*** income which results from the response of federal and state policies. In effect, our results reflect effective marginal tax rates as presented in Maag et al. (2012), Holt and Romich (2007) or Congressional Budget Office (2012), for different years and states. In this section, we provide details on the simulation model and the experiments we employ it for. We also describe the prototype family we refer to as our household of interest, report our data sources and present the measure of insurance which we compute from the experiments.

3.1 Modelling Household Insurance

We start our investigation from the most general representation of a household's income and spending opportunities, i.e. the household budget. In any period t, the associated equation can be written as

$$w_t + a_{t-1}r = c_t + (a_t - a_{t-1}) \tag{1}$$

where w_t denotes gross (before tax and transfer) labor income, a_{t-1} is the amount of savings the household set aside in the previous period (so $a_{t-1}r$ is the net return earned on those savings) and c_t denotes consumption expenditures. Finally, $a_t - a_{t-1}$ reflects the household's change in its net asset position. In other words, if $a_t - a_{t-1} > 0$ the household increases its assets relative to the previous period, while it reduces them if $a_t - a_{t-1} < 0$. We proceed by noting that gross labor income is the sum of household transfers b_t, labor income taxes τ_t and disposable (after tax and transfer) labor income y_t. If we further index taxes and transfers by governmental level $l = \{s, f\}$, we can express gross labor income as

$$w_t = y_t + b_t^s(w_t) + b_t^f(w_t) - \tau_t^s(w_t) - \tau_t^f(w_t) \tag{2}$$

where, for the sake of exposition, we assume taxes to be always positive for now but we relax this assumption later to account for tax credits in our experiment. Note that in this exposition, we explicitly list transfers and taxes as functions of gross labor income. For reasons of notational convenience, we drop their arguments from now on.

Substituting terms, we re-write equation (1) as

$$y_t + b_t^s + b_t^f + a_{t-1}r = c_t + \tau_t^s + \tau_t^f + (a_t - a_{t-1}) \tag{3}$$

where those variables which typically represent sources of income are on the left hand side, and those which are commonly expenditure items are on the right hand side. We assume the interest rate r to be time-invariant. For the purpose of our investigation, this assumption is easily justified: we are interested in the response to an unexpected labour income shock which is specific to a single family. Hence, this shock does not affect aggregate variables such as the return on savings. Moreover, as our object of interest is a single household, it seems natural to assume that changes to its net asset position do not affect the interest rate.

To simplify equation (3), we define net transfers received from government level as $T_t^i = b_t^i - \tau_t^i$ where we allow T to take any sign. Applying this definition and reordering terms we can re-write the above equation as

$$y_t = c_t - T_t^s - T_t^f + a_t - a_{t-1}(1+r) \tag{4}$$

Next, we iterate forward by one period so the equation becomes

$$y_{t+1} = c_{t+1} - T_{t+1}^s - T_{t+1}^f + a_{t+1} - a_t(1+r) \tag{5}$$

From now on, we conceptualize the difference between labour incomes in consecutive periods as a shock. We denote this shock as $\varepsilon_t = y_{t+1} - y_t$ and use the difference operator Δ to rewrite it as $\varepsilon_t = \Delta y_t$.

Finally, we subtract item by item of equation (4) from equation (5) which yields

$$y_{t+1} - y_t = c_t - c_{t+1} - T_t^s - (-T_{t+1}^s) - T_t^f - (-T_{t+1}^f) \tag{6}$$
$$+ a_t - a_{t+1} - a_{t-1}(1+r) - (-a_t(1+r)) \tag{7}$$

Using the difference operator as defined above, this equation can be written as:

$$\varepsilon_t = \Delta c_t - \Delta T_t^s - \Delta T_t^f + \Delta a_t - (1+r)\Delta a_{t-1} \tag{8}$$

We can now discuss the channels of insurance which are available to a household facing a shock to earnings, and outline in detail which channels we explore in our experiment. We identify two types of channel: public insurance and private insurance.

1. **Public insurance** – resulting from government policies. We assume full tax compliance and benefit take up by the household and we abstract from the policies of local (i.e. municipal or county) governments.

   - Income taxes (τ) – we include state and federal tax credits in this category and thus allow taxes to be either positive or negative, where a negative tax payment corresponds to receipt of a tax credit
   - Transfers (b) – receipts from means tested welfare programmes administered by the federal and state governments. These can only take positive values.

   In subsequent sections of the paper, we will refer to *net transfers* T as defined above, i.e. the difference between transfers received and taxes owed.

2. **Private insurance** – resulting from household decisions. Our experiment does not include these channels but we outline their potential sources and the modelling assumptions under which they might be restricted.

   - Asset positions (a_t) or asset income (ra_t) – we think of the household as being hand-to-mouth in the sense of not having (liquid) assets which it can use to smooth consumption. The household is also not able to adjust asset *income* which we think to be exogenous from the perspective of the household.
   - Change in labour decision – we assume that labour inputs are fixed before the earning shock so that the household cannot smooth the shock by adjusting hours worked.

- Migration – we treat the household is immobile, so that it cannot react to the shock by, for instance, moving to a different job in a different state.

As detailed above, our experiment is equivalent to shutting down the private channels of insurance, allowing the incidence of the earnings shock to be absorbed only by changes in net transfers. Any unsmoothed shocks are then mechanically absorbed by changes in consumption[7] As such, the insurance measures which we present can also be thought of as lower bounds on the smoothing which a household can achieve in each state. Our decision to ignore private smoothing channels is only important for our question if these channels differ systematically across states. For example, it could be that the ability to insure using private asset portfolios varies systematically between states. Overall, there is little evidence this could be a concern for the United States. In this regard, we want to mention that Hintermaier and Koeniger (2016) show that differences across states in homestead exemptions in bankruptcy procedures have small effects on welfare compared to a fully harmonized system.

Another possible objection to our analysis is that we do not account for mobility decisions of households as a response to changes in local earnings opportunities. In general, empirical evidence suggests that population adjustments between cities and states in response to local labour market shocks occur over long time horizons and are small (Blanchard and Katz, 1992; Glaeser and Gyourko, 2005). For example, Autor et al. (2013) examines the local labour market effect of increased Chinese import competition in the US; they find that the migration response is small even for regions which are highly exposed to imports. Moreover, several recent papers – examples are Kaplan and Schulhofer-Wohl (2017) and Johnson and Kleiner (2017) – have found a steady decrease of interstate migration which may be due to increasing costs of mobility (e.g. housing, occupational licenses, non-portable transfers or pension schemes).

Regarding the type of shock and family our simulation covers, work by Kennan and Walker (2011) as well as Austin et al. (2018) shows that our assumption regarding immobility is plausible. On the one hand, Kennan and Walker (2011) found that migration decisions are mostly a response to permanent shocks to income. Moreover, they typically occur at specific stages of the individual life cycle, e.g. in the context of college attendance decisions. On the other hand, Austin et al. (2018), relate the persistence of labour market drop out rates in low wage areas to increased real estate rents in areas with high wages; they show that poor households cannot migrate to search for employment in highly productive areas as the local accommodation rates exceed their budgets. Hence, US domestic migration is more and more concentrated among workers who change jobs in high-skilled sectors. As we consider our prototype family to be working poor, abstracting from mobility decisions in the context of our experiment does therefore not omit a significant source of insurance.

Obvious omissions from this analysis are unemployment insurance and social security systems. We choose not to include these because their eligibility and benefit levels depend on the individual's history of labour market participation and social security contributions. We therefore do not see these as providing *unconditional* protection against a reduction in income; instead they function more as a (subsidized) form of self-insurance which is managed by the government.

[7] This link between changes in consumption and changes in disposable income can also be derived by assuming that the household is liquidity constrained, i.e. wealthy hand-to-mouth using the terminology of Kaplan et al. (2014).

Table 23 provides a summary of the relative fiscal magnitude of the programs we include in our simulation. Regarding unemployment insurance, this table shows that public expenditures on this program are actually relatively small compared to those which we do include[8].

3.2 The Prototype Family

In order to capture correctly the changes in tax liabilities and transfer entitlements, we consider a household with fixed characteristics across years and states. Assigning specific characteristics is necessary as the sources of insurance we study depend not only on income but also on other features of household composition. For taxes, a critical determinant of liabilities and credits is the number of dependants of a tax filer and whether a couple is able to file jointly. In addition, the presence of children in the household grants specific child tax credits and deductions for childcare expenses. Mortgage expenditures and pension incomes are also deductible items.

Household characteristics are equally important for determining eligibility and generosity of the transfer programs we consider. For SNAP and AFDC/TANF the number of family members is a critical parameter. For Medicaid, a key element of the heterogeneity in eligibility across states is the extent to which children are covered. Hence, it is necessary to fix the ages of the children. For these reasons, our prototype family remains invariant throughout our microsimulation exercise with respect to relevant characteristics, listed as follows:

- A married couple with two children between ages 4 and 7
- Family income from two equal full time labour incomes
- No disabilities
- The family home is rented (no mortgage payments)
- No other family members occupy the home
- The family does not migrate as a response to changes in earnings

The advantage of our approach is that it allows us to capture differences in insurance provided by combined federal and state net transfers using a consistent benchmark. If we were to change family characteristics our results would be less informative for our research question. On the one hand, they would confound the differences we are interested in with potential differences in state government preferences over specific family types.[9] On the other hand, if 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 from state policies consistently.

3.3 The Subsistence Basket

For a given year, we locate our prototype household in a particular state and allocate a pre-tax income level which depends on the specific experiment. To convert the nominal pre-tax income

[8]This does not necessarily apply to all years in the period considered in our experiment as emergency federal contributions during severe recessions can cause unemployment insurance to be quite substantial.

[9]For now, we choose to ignore the possibility that differences in state policy arise from variation in the composition of the average household in each state. Such variation might be the result of a median voter theory on the determination of state welfare policies. We explore this issue in the discussion of our results.

into comparable consumption units, we use a subsistence expenditure basket. We calculate this subsistence expenditure as the sum of two components. The first is the minimum required level of monthly food spending as stated by the federal Thrifty Food Plan, a US government measure which specifies the minimum amount which a family of a given size needs to spend to consume a nutritious diet. We list the nominal amounts and the data sources in the appendix. The second is the average monthly rent payment for households in the same state with similar characteristics and income. We consider both of these components as fixed costs for the household, in the sense that once a shock to income is realized, the household cannot respond by forgoing these expenditures.

We obtain the conditional average monthly rent from the American Community Survey (ACS)[10] for each year and state by taking households from the state in question with similar income and demographic characteristics as our prototype household. In general, we take households within a 5 percentile band of the prototype household in the state income distribution. As an illustration, if the prototype household is at the 10th percentile of California's income distribution, we take all households in California between the 5th and 15th percentiles and alsocondition on marital status and family size, as well as the number and ages of children. We then average gross monthly rents across families who reported incomes within these groups for a given year and state.[11]

3.4 Simulation

We subject the household's pre-tax income to a shock, which can be positive or negative. In our first experiment, the size of the shock will be calculated as a number of subsistence baskets, so that we can equalize the shock size in real terms across states. Our results measure the on-impact response of tax and transfers.[12] We can then compare disposable income (i.e. income adjusted for taxes paid and transfers received) at the pre-shock and post-shock levels. This exercise is repeated for all US states in different years.

Using the notation introduced earlier, for a pre-tax labor income in state s of w_0^s, the value of

[10] The ACS variable which we use for rent (RENTGRS) is 'gross monthly rental cost of the housing unit, including contract rent plus additional costs for utilities (water, electricity, gas) and fuels (oil, coal, kerosene, wood, etc.)' This makes the variable more comparable across households than net rents and, as our aim is to capture all household expenditures related to housing, this variable is ideal for our purposes.

[11] Official measures of representative rents are computed in a similar way; for example, the Fair Market Rents (FMR), which are estimated by the US Department of Housing and Urban Development (HUD), correspond to the 40th percentile of the distribution of monthly rents of all units occupied by rent movers in a specified geographic area. As we are interested to estimate results for households with low incomes we condition their average rents on the income distribution as described above. In some rare cases, our collected average rents flucturate substantially from year to year. The reason for these anomalies are low number of observationss. For those state and year cells, we widen the bands of the incomes to the 2 and 18 percentiles, respectively. We then replace values which are below or above 20% of the corresponding FMR value. We report on these procedures in more detail in the appendix.

[12] Since we are simulating an idiosyncratic shock to a selected household, we also avoid any endogeneity problems by which the policy choices at the state or federal level might respond to the change in economic conditions. As discussed by Bourguignon and Spadaro (2006), this is a key advantage of using a simulation approach to evaluate the effects of policies.

pre-tax income after the shock is given by[13]:

$$w_1^s = w_0^s + \varepsilon \tag{9}$$

The pre-shock and post-shock disposable incomes, y_0^s and y_1^s are then given by:

$$y_0^s = w_0^s - \tau^f(w_0^s) - \tau^s(w_0^s) + b^f(w_0^s) + b^s(w_0^s) \tag{10}$$

$$y_1^s = w_1^s - \tau^f(w_1^s) - \tau^s(w_1^s) + b^f(w_1^s) + b^s(w_1^s) \tag{11}$$

3.5 Policy Calculators

In order to impute the taxes and transfers associated with different gross labor incomes in different states and years – as shown in equations (10) and (11) – we construct a simplified version of the US tax and transfer system. To cover the main income support programs, we apply a combination of previously available calculators and design a new calculator for SNAP. We impute Temporary Assistance for Needy Families (TANF, formerly Aid to Families with Dependent Children) and Medicaid benefits by employing the calculators used in the paper Hoynes and Luttmer (2011)[14]. Compared to TANF and Medicaid, the eligibility and benefit parameters of SNAP (formerly Food Stamps) are much easier to model and we design a calculator ourselves. We provide further details on the calculators, including references and data sources, in the appendix. We impute taxes by using TaxSim. This software covers both federal and state income taxes and, most importantly,includes Earned Income Tax Credits (EITC) of fiscal administrations from both levels as well as state specific child tax credits. As TaxSim is widely used for the purpose of imputing income taxes, we defer a more detailed discussion on its accuracy to the appendix. Taken together, the transfer and tax programs covered by our simulation model account for large proportion of welfare spending in the US. Their relative contributions to total expenditure are summarized for the year 2007 in figure 25 shown in the appendix.

3.6 Our Insurance Measure

For each of the experiments we consider several shock sizes ε_i, $i = 1, 2, \cdots, N$. Our measure of the insurance provided by the combined tax and transfer system in state s:

$$\chi_i^s = 1 - \frac{y_0^s - y_{1,i}^s}{\varepsilon_i} = 1 - \frac{y_0^s - y_{1,i}^s}{w_0^s - w_{1,i}^s} \tag{12}$$

Thus, 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 against the shock; conversely if disposable income does not decline at all, χ will be one, indicating full insurance. Intermediate values indicate partial insurance[15]. More generally, if household *pre-tax* income undergoes a

[13] Here we suppress notation referring to the characteristics of the household, which will also determine eligibility for welfare programs and income tax credits. As explained above, we hold the relevant characteristics of the household fixed throughout the exercise.

[14] They have been provided to us by Hilary Hoynes and Erzo Luttmer which we gratefully acknowledge.

[15] It is possible for states to have values above 1, in which case after tax transfers increase more than the amount of the shock, and negative values, which indicate that disposable income actually falls more than the value of the shock.

negative shock of one subsistence expenditure basket, $1 - \chi$ is the number of baskets lost from *disposable* income due to changes in state and federal taxes and transfers.

After calculating the net transfer policy responses for different shock sizes, it will be useful to calculate a single measure which summarizes the level of insurance for a particular state in a given year. We do this by calculating an average of the insurance measure χ_i^s across shock sizes ε_i, weighted by the shocks themselves. We define the average insurance measure $\bar{\chi}^s$ for state s:

$$\bar{\chi}^s = \frac{\sum_{i=1}^{N} \varepsilon_i \chi_i^s}{\sum_{i=1}^{N} \varepsilon_i} \tag{13}$$

It is also informative to break down the relative contributions of the federal and state governments, which should allow us to explore the extent to which state government policies drive the differences in outcomes. For government level $l \in \{s, f\}$, in state s we define $\chi_i^{s,l}$ as

$$\chi_i^{s,l} = \frac{\tau^l(w_0^s) - \tau^l(w_{1,i}^s) + g^l(w_{1,i}^s) - g^l(w^0)}{\varepsilon_i} \tag{14}$$

which is the ratio of the change in net transfers from government level i to the income shock.

3.7 Our experiments

With this framework in place, we conduct two different experiments:

1. Give the household a pre-tax and transfer income which in each state has the same real value as the Federal Poverty Line (FPL). We find this income as follows: We compute the nominal cost of a 'national' subsistence basket using the procedure described above except that we do not condition on state of residence. Hence, the nominal cost of this basket reflects the monthly rent and food expenditures averaged across all US states. Next, we divide the FPL value for a family of four by the cost of this basket. For example, for the year 2004, this corresponds to a number of 34 baskets. Finally, we give the family a nominal pre-tax and transfer income w_0^s in each state s such that it can afford 34 baskets. We then subject this income to a shock of ε baskets. Thus, when we vary the shock size ε_i, we are considering different numbers of subsistence expenditure baskets. We vary the shock size in steps of 0.5 baskets between -5 baskets and +5 baskets.

2. Give the household a pre-tax and transfer income w_0^s which corresponds to the 10th percentile of the income distribution in each state (and year) and subject it to a shock of ε%. Thus, when we vary the shock size ε_i we are taking away (or adding) different proportions of the initial income. We vary the shock size in steps of 5% from -20% to + 20%.

The first experiment is the closest to answering our research question, which is to what extent the federal system implies differential insurance conditional on state of residence. The second experiment aims to explore the results of the first in more detail and to account for difference in states policies. As the real income of a household who is poor *relative to its state peers* differs across states, state policies to help low income households could be targeted towards households with different real incomes across states.

4 Results

In this section we present the results of our two main experiments.

Experiment 1 (Fixed Real Income) The main results of the first experiment are shown in figures 7, 8 and 9 for the year 2004. Figures 7 and 8 show the responses in different states to a negative income shock equivalent to 3.5 subsistence baskets, i.e. 10% of pre-tax number of baskets. To help build intuition, we begin by describing the results in terms of the number of consumption baskets lost from disposable income in Figure 7. This varies from a minimum of roughly 1.9 baskets in Oregon to a maximum of just over 3.2 baskets. Thus, while in states with very high insurance almost half of the negative earnings shock is absorbed by changes in net transfers, in most states almost all of the shock is reflected in disposable income. Figure 8 shows the same results in terms of our insurance measure χ_s, which varies between 0.07 (Idaho) and 0.46 (Wisconsin), with most states falling between 0.05 and 0.15.

In Figure 9 we consider a more robust measure of the level of insurance in each state by plotting the decomposition of state insurance contributions against federal contributions, averaged across the different shock sizes as described in the previous section [16]. In this plot, states with higher *total* insurance are also represented by larger circles, while the colours of the circles indicate how high living costs are in each state. In this figure a clear group emerges of states with relatively high total insurance made up of large contributions from both levels of government: these states are Wisconsin, Oregon and New York (they are also joined by the District of Columbia). Below these there is another larger group of states which have high total insurance which is mostly provided by net transfers from the Federal government. This second group includes Washington, Nevada, California, Virginia and Delaware among others.

To determine the drivers of these results we look more closely at the two sources of variation in this experiment: net transfer policies and nominal incomes. Recall that nominal incomes differ because while we give the household the same number of subsistence baskets in each state, the nominal cost of these baskets varies by state. In Figures 10 and 11 we plot SNAP and Medicaid entitlements before and after a negative earnings shocks of 3.5 subsistence baskets. In Figure 10 we see that all states experience an increase in SNAP entitlements; importantly, in no state are the SNAP entitlements exhausted after the shock. In proportional terms, those states which begin with a low level of SNAP entitlement before the shock experience the largest increase in entitlements. Thus, for states like New York, Oregon, Nevada, Washington and New Jersey, the increase in SNAP entitlements makes a large contribution to insurance from the Federal government, although as we will see, the cash amounts involved are relatively small compared to changes in tax liabilities. Medicaid does not seem to be an important insurance source for the high insurance states. In Figure 11 we see that in the vast majority of states, the household does not experience any change in its Medicaid entitlements. However, this figure does identify a small group of states which start with relatively low Medicaid entitlements and then display a very steep increase after the shock. This group includes Colorado, Mississippi, Utah, Tennessee and Texas. This strong response of Medicaid entitlements places many of these states in a middle group in Figure 9 of states with above average total insurance and a federal insurance contribution close to 0.15.

[16] The complete set of decompositions for each state and each of the different shock sizes can be found in Appendix B

In Figures 12 and 13 we see the response of state and federal income taxes in the same experiment, noting that negative amounts refer to tax *credits.* Federal income tax policy, which at this income level refers to the EITC, is much more responsive for the high insurance states identified in Figure 9, as can be seen by their distance from the 45 degree line in Figure 12. Given the design of the EITC, this must mean that in these states the household is located slightly above or on the 'phase out' portion of the EITC schedule, so that its earnings and credit entitlements move in opposite directions; this in turn results from the fact that it has a relatively high *nominal* income because living costs in these states are high. In Figure 12 this can be seen that the fact that the response are completely ordered by the level of living costs in each state.

State income tax liabilities, on the other hand, seem to be much less responsive, with most states levying close to zero taxes on the household both before and after the shock. Oregon and New York, however, are among the states which offer the largest decrease in tax liabilities in response to the shock, which partly explains why the contributions of both state and federal government net transfers are relatively high in these states.

Overall, the results of this experiment point to the fact that households with low real incomes living in expensive states have low Federal entitlements before receiving the shock, as we would expect from the nominal uniformity of federal policies. However, Federal policies then become a very important source of insurance in response to a negative income shock for these households as they become eligible for increased SNAP benefits and EITC payments. Conversely, household with low real incomes living in cheap states, which by construction also have low nominal incomes, have already exhausted most of their entitlements before receiving the shock. They therefore do not receive much insurance in response to an income shock. There is also a small group of states like New York, Oregon and Wisconsin in which low income households receive extra insurance due to the progressivity of the state income tax schedule. In the majority of states, the household relies mostly on increases in SNAP entitlements for insurance against income shocks. A handful of states also offering increased Medicaid entitlements, which reflects the fact that they had not yet exhausted their benefits before receiving the shock.

We note that while the real income level we have chosen for this experiment is relatively low, it does not necessarily put the household at the bottom of the income distribution in each state. This is important because one possible explanation for the pattern of results which we find could be that states like California and Nevada target their welfare policies towards households with even lower incomes than the level which we investigate; conversely, in New Hampshire the household would be one of the poorest in the state, and so we would it expect it to receive higher net transfers. We explore this explanation in the next experiment.

Experiment 2 (Fixed state income percentile) Figures 14 and 15 illustrate the average insurance measure $\bar{\chi}_s$ by state for the years 2001 and 2008. We compare different years to see how stable the insurance contributions are over time. In both of these figures we see that there is much more variation across states in total insurance than we found in Experiment one, with $\bar{\chi}_s$ ranging from close to 0 to just below 0.6 in the most generous states, where the value of 0.6 indicates that more than half of the shock to earnings is absorbed by public insurance. Compared to the first experiment, some new states emerge as high insurance locations for households at the 10th percentile of the state income distribution. As well as New York, we now find that

Kansas, Iowa and Wisconsin are generous states. This is shown in Figure 17 where we average $\bar{\chi}_s$ over time to derive a measure of insurance for each state over the period 2001-2008. We also see here that households at the bottom of the income distributions of Idaho, Montana, New Mexico, Texas and West Virginia received very little total insurance over this period.

Figure 16 decomposes these total insurance measures into state and federal contributions. Again, for each state the size of the circle indicates the amount of *total* insurance while the colour of the circle indicates the cost of living in that state as indicated by the price of the subsistence baskets. A key question for our analysis is whether the level of insurance provided by the state government becomes more similar when we give the household nominal incomes corresponding to the 10th percentile of each state's nominal income distribution. It is clear from the figure that this is not the case - the average state insurance contribution now ranges from 0 to 0.15, an even wider range than in the previous experiment. The variation in state insurance levels seems to be increasing in the level of federal insurance - at the maximum federal insurance contribution (close to 0.3), the state contribution varies between 0 and 0.15.

There is also no obvious pattern in the relationship between the cost of living and the level of insurance, although we do see that the states with the highest insurance from federal net transfers are predominantly cheap states. Also, it appears that in cheap states , the household enjoys less total insurance than in medium and expensive ones (as the blue circles are generally smaller). In fact, the group of states in which the household receives significant assistance from both levels of government is also larger than in the first experiment, and now includes Minnesota, Kansas, Vermont and Iowa. With the exception of Iowa, these are all medium or expensive states.

In this experiment we again have two potential sources of variation - differences in the level of state income distributions and geographical differences in net transfer policies. We try to separate the contributions of these factors by inspecting the individual policies which we simulate. An important observation is that living costs are positively correlated with the average level of nominal income in each state; thus households which live in expensive states also tend to be richer in nominal terms. As a result of this, the overall pattern of transfer responses is quite similar to that of the previous experiment. Figures 18 and 19 display the transfer response to a negative shock of 10% of earnings in the year 2004. In Figure 18 we see that in all states, the household receives an increased SNAP entitlement in response to the shock. This increase is large in percentage terms in states where the SNAP entitlement was low before the shock was received. These states tend to fall in the Expensive and Medium living cost categories. Compared to the first experiment, there are also more states which start with zero SNAP entitlement and move to a positive amount after the earnings shock, including Colorado and Maryland.

Figure 19 shows that at the income levels which we consider, the household's Medicaid benefits have already been exhausted in most states, so that they cannot respond to the earnings shock. However, there are again some more expensive/high income states where Medicaid benefits move from zero to a positive amount. In the cases of Connecticut and Illinois, the cash amounts are quite substantial, contributing around \$340 and \$200 to disposable income respectively.

In this experiment we find that EITC payments play a very important role for low income households in almost all states. We see this in the fact that the federal contribution levels in Figure

16 are generally higher than those in Figure 9. Figure 20 shows the response of these payments to the earnings shock. An interesting feature of this graph is that since the Federal income tax system is progressive and uniform across states, the states are ordered from left to right by the nominal income of the household at the 10th percentile of the state income distribution. The correlation between living costs and the level of nominal income is also clear in this figure. We see that there is a small number of states, like Wyoming and New Mexico, where income levels are so low that our chosen household is on or close to the plateau of the tax credit schedule; as a consequence, the credit amounts do not respond much to the negative earnings shock because the shock is small in absolute terms. In most states, however, the household experiences a large increase in its tax credit entitlement [17].

Figure 21 presents change in state income tax liabilities (or tax credit entitlements) in response to the earnings shock. Unlike in the first experiment, we see that state income tax progressivity provides insurance in most of the states. In all but a few states, the tax liability decreases; among the exceptions are New Mexico and Arizona, which provide constant tax credits to households at this income level. Amongst the other states, we can identify some like New York, Kansas, Vermont and Wisconsin which provide a relatively large increase in state income tax credits after the shock; we can also identify another group, made up of areas like Maryland, Massachusetts and DC, which levy positive taxes both before and after the shock, but which reduce the tax burden by a relatively large amount after the shock. All of these states which display high tax progressivity are in the Medium and Expensive living cost groups. This partly explains the pattern which we observe in Figure 16 - a positive correlation between state living costs and total insurance.

[17] We note that for some of the richer states - Connecticut, New Hampshire and New Jersey - the response of EITC is somewhat muted compared to the rest of the sample. We are not yet able to explain why this happens. It may result from an imputation error in TaxSim or a nonlinearity in the phase out portion of the EITC schedule

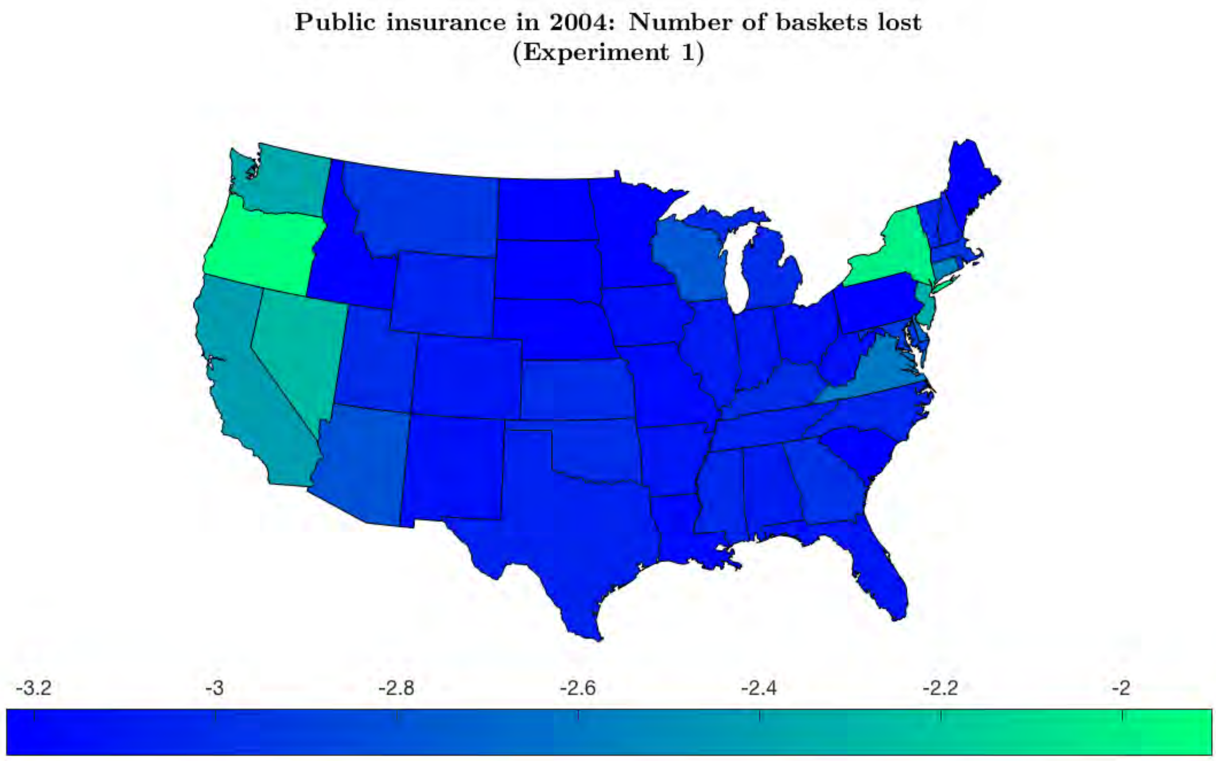

Figure 7: Experiment 1 - Baskets lost

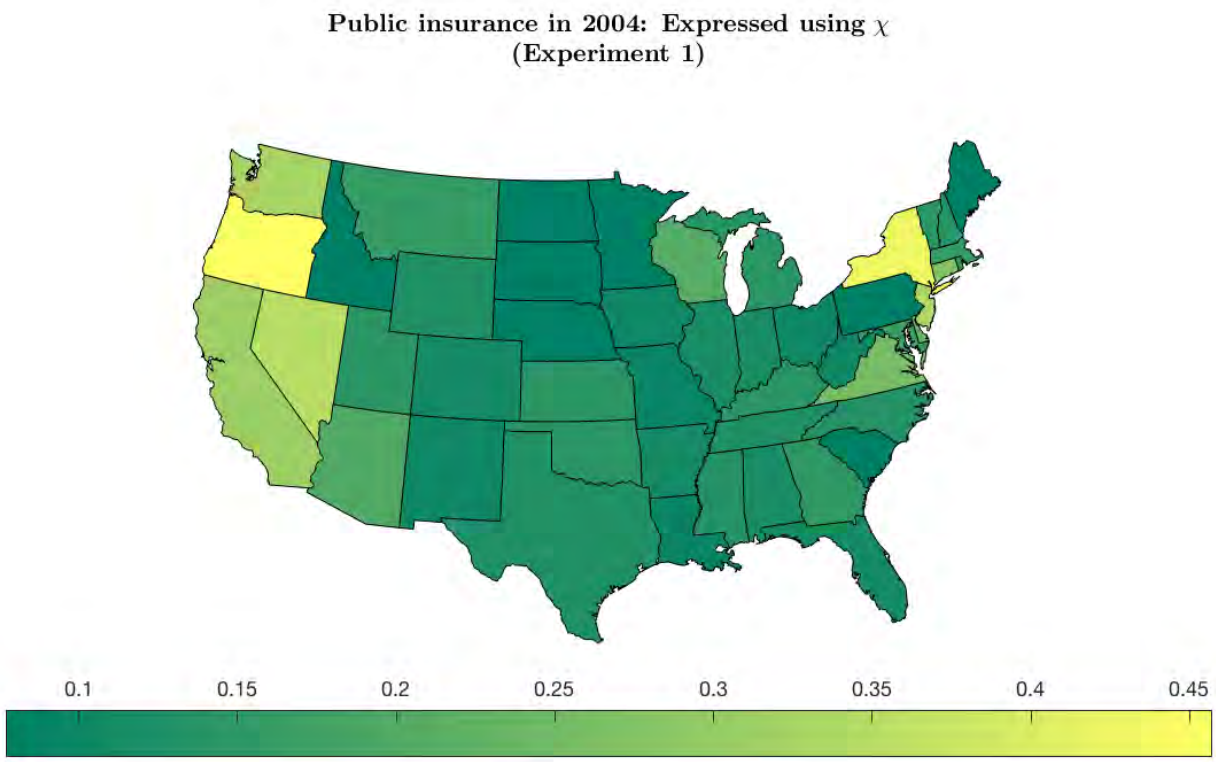

Figure 8: Experiment 1 - Insurance Measure

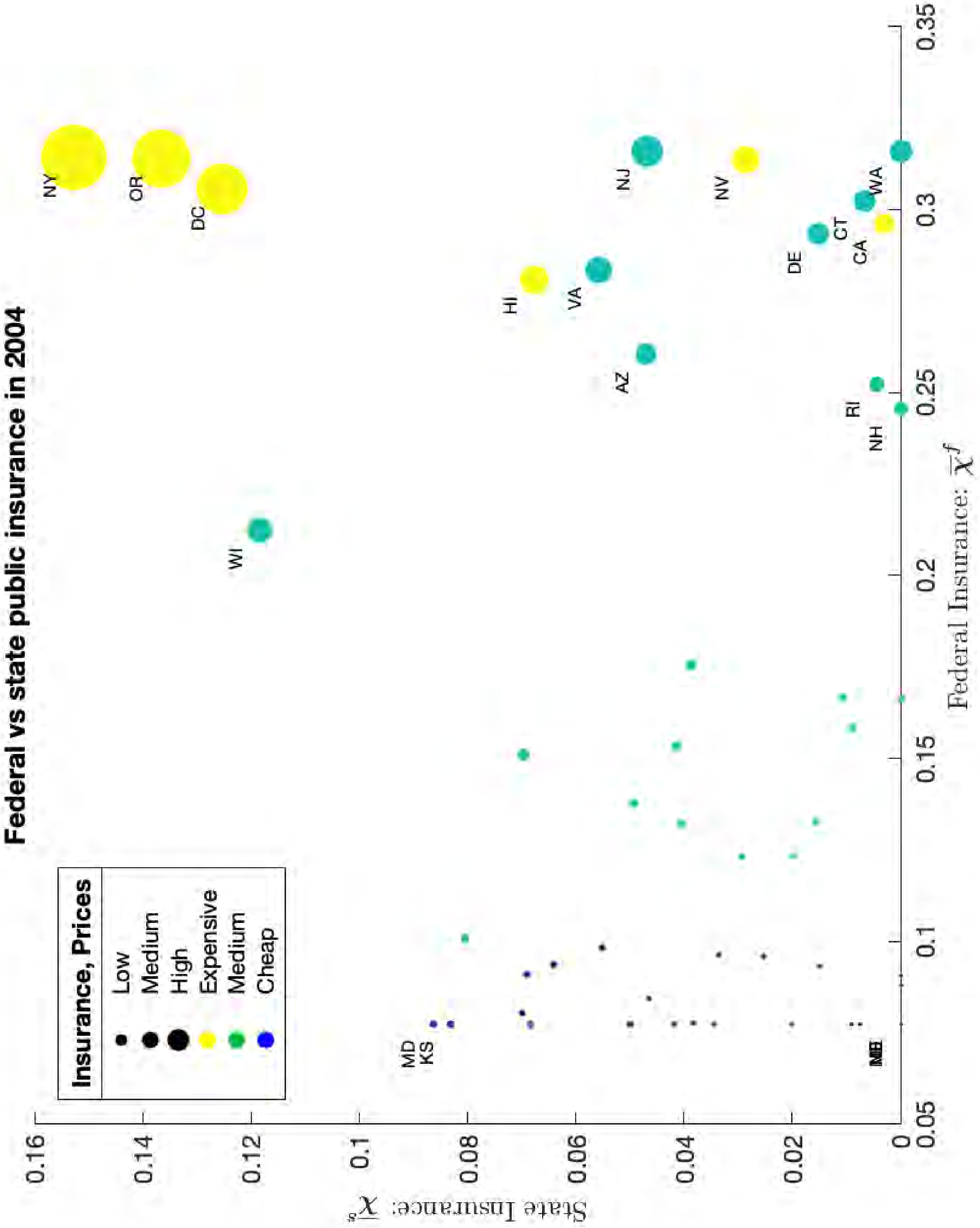

Figure 9: Experiment 1 - Relative contributions

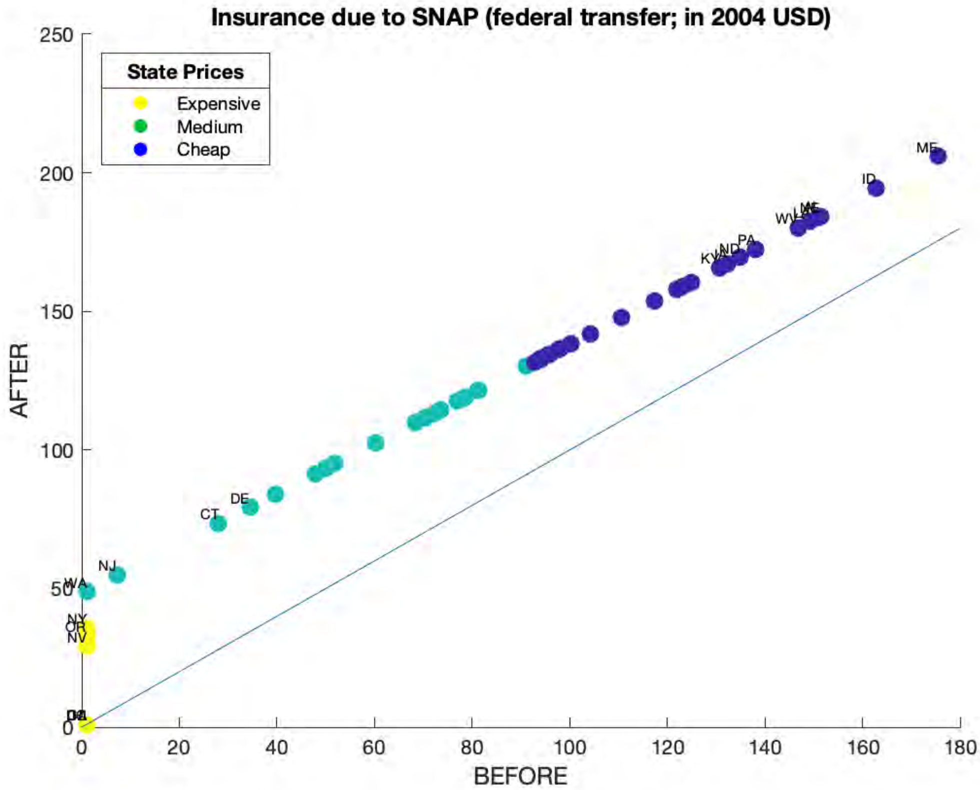

Figure 10: Experiment 1 - SNAP benefits

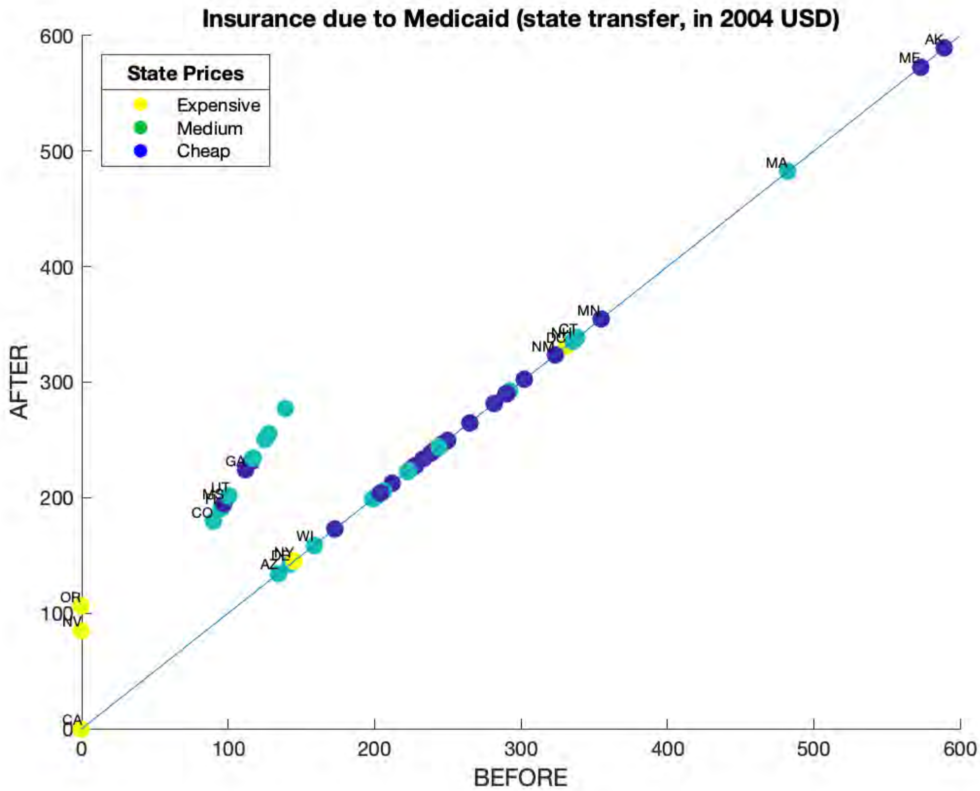

Figure 11: Experiment 1 - Medicaid Benefits

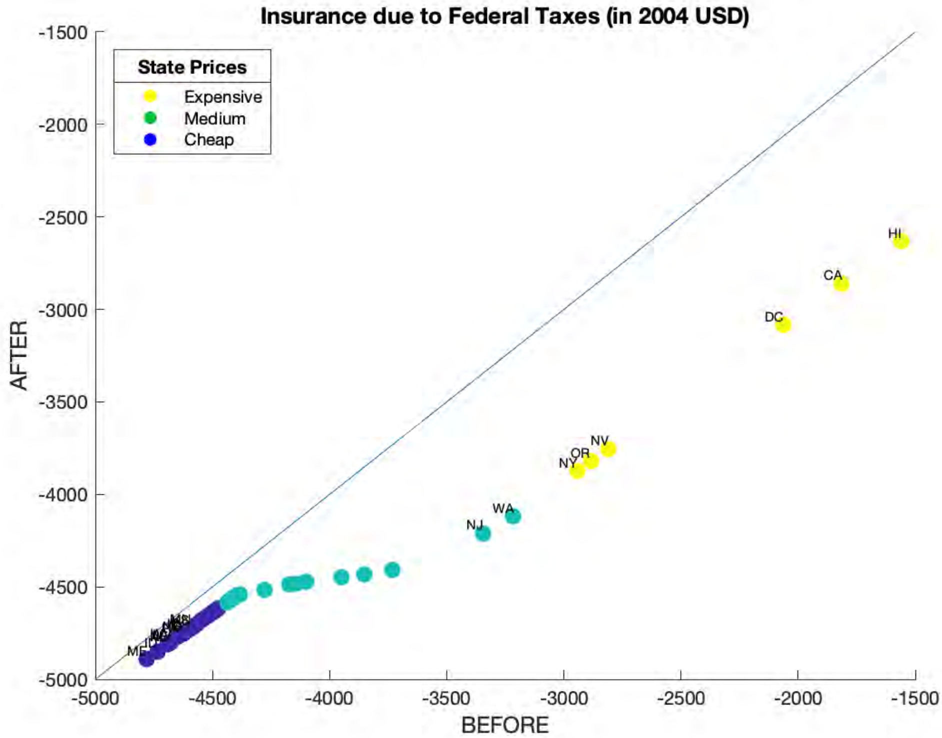

Figure 12: Experiment 1 - Federal Income Taxes

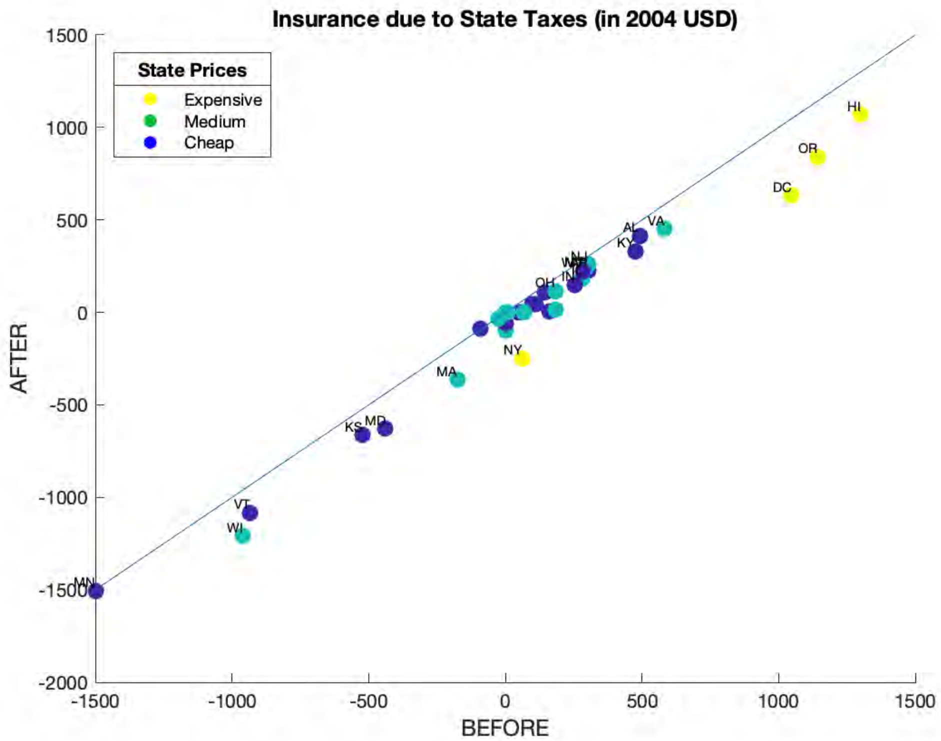

Figure 13: Experiment 1 - State Income Taxes

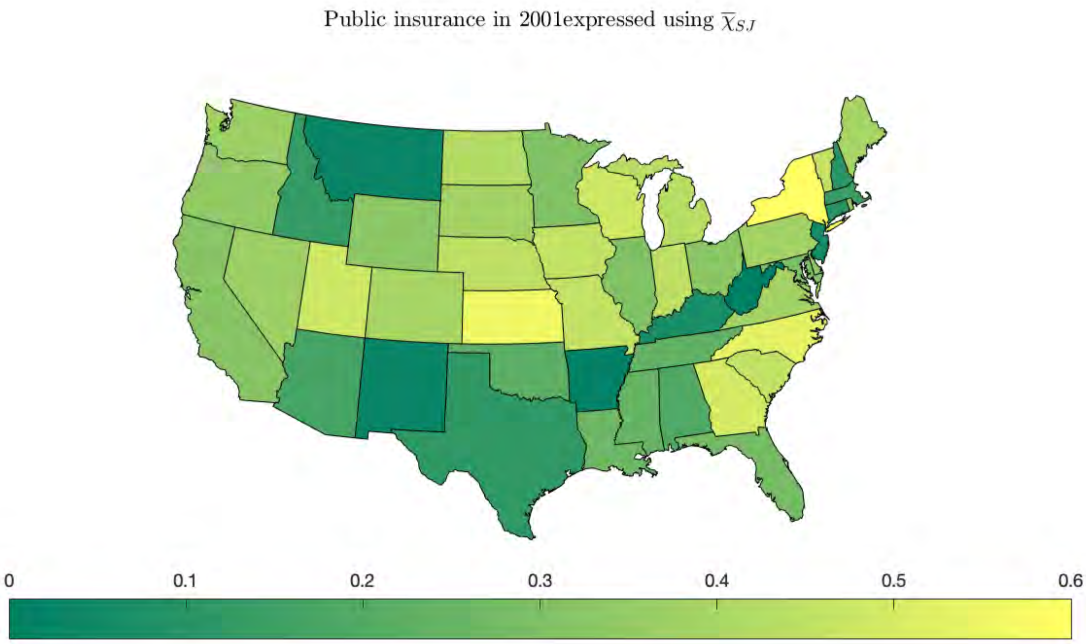

Figure 14: Experiment 2 - Insurance values, 2001

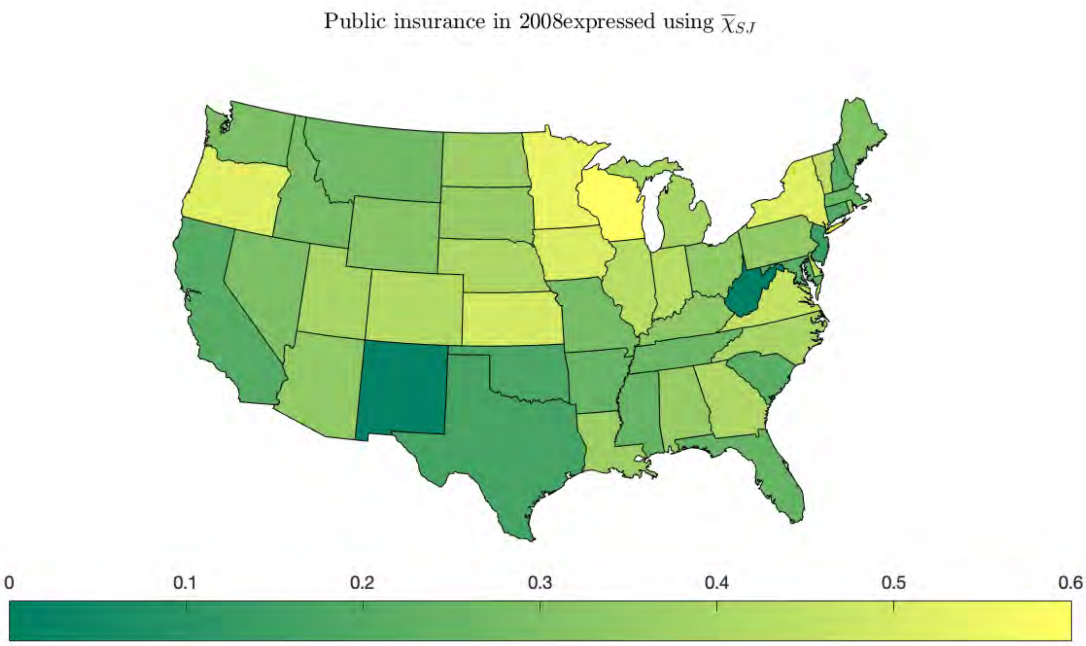

Figure 15: Experiment 2 - Insurance values, 2008

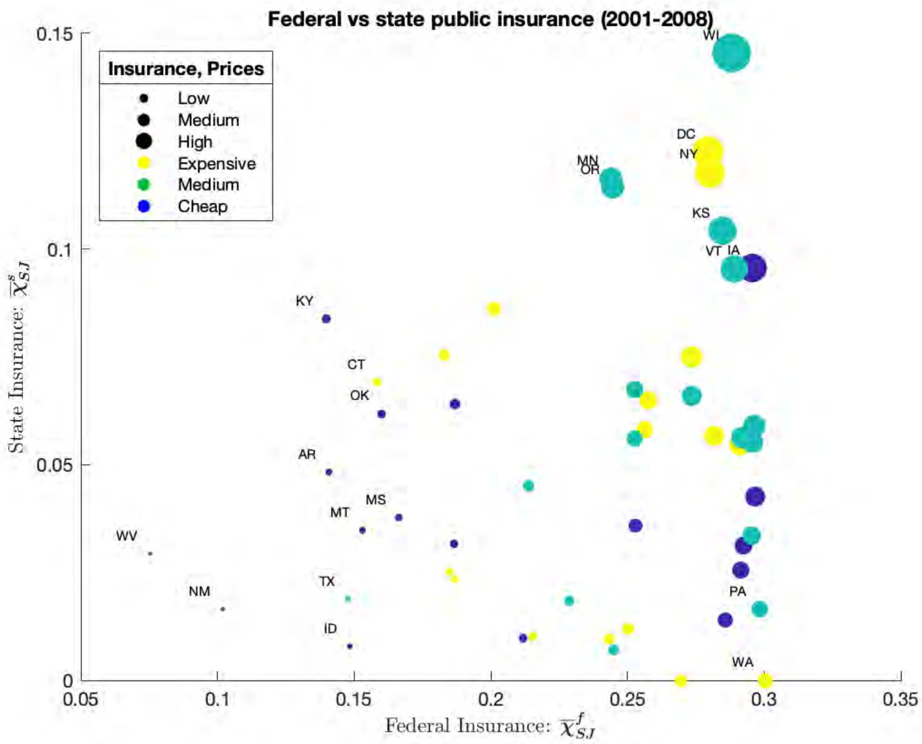

Figure 16: Federal contribution against state contribution, averages over shock size and time

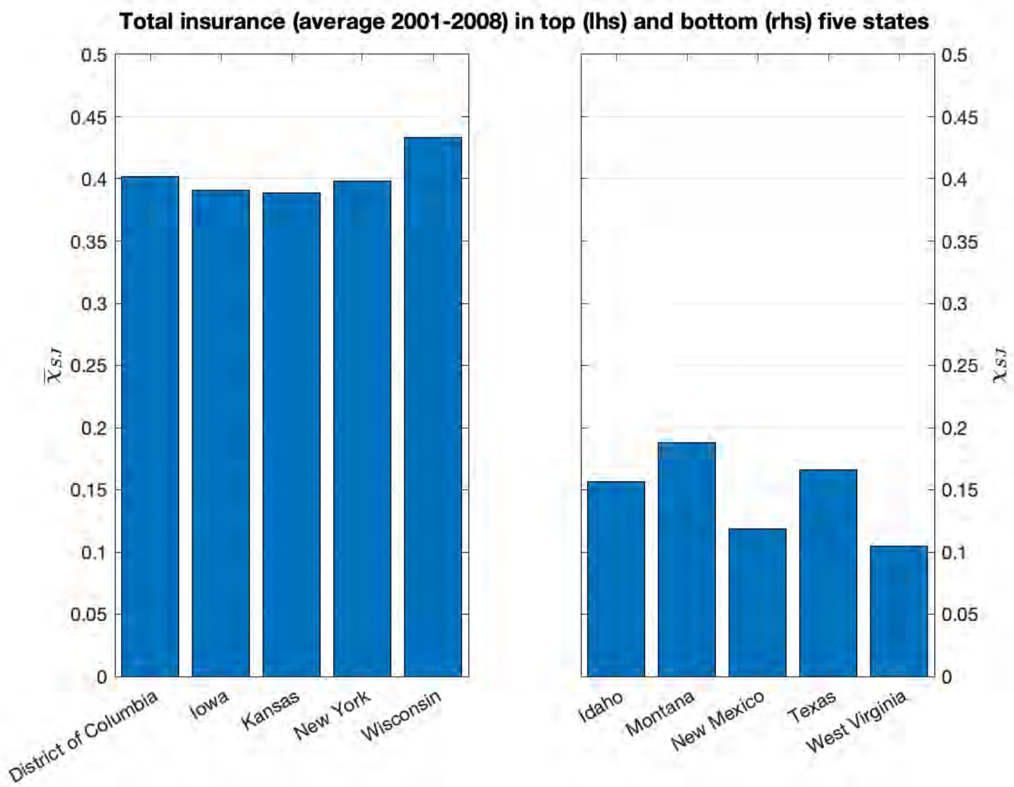

Figure 17: Overall insurance, highest and lowest insurance states

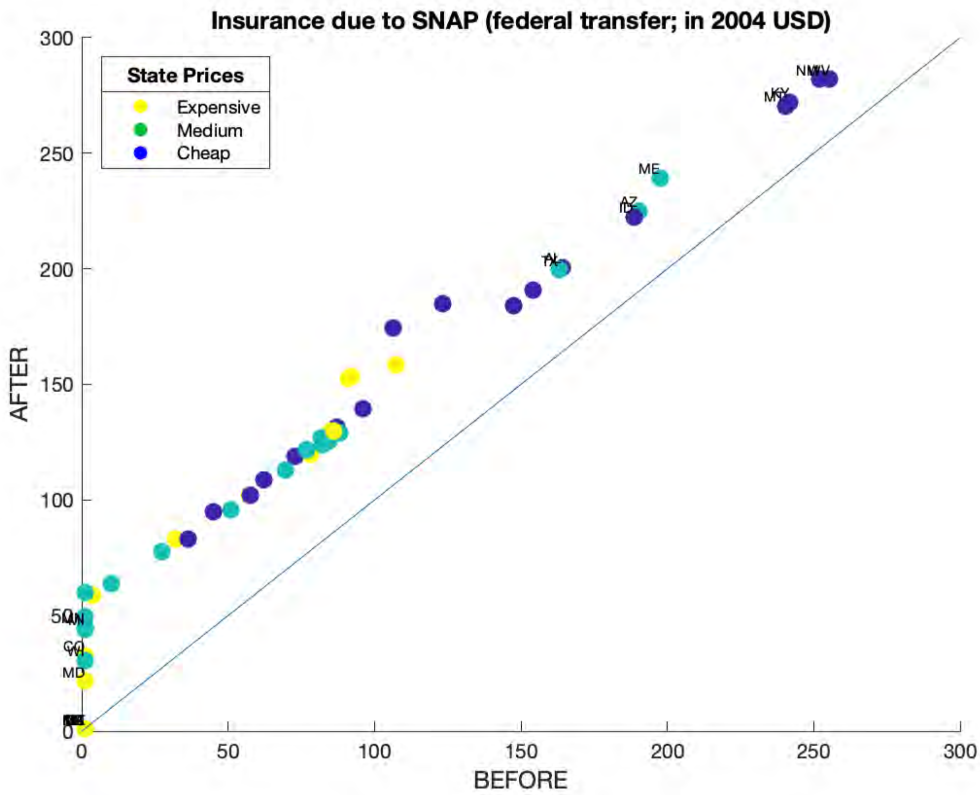

Figure 18: Experiment 2 SNAP benefits for a negative earnings shock of 10%

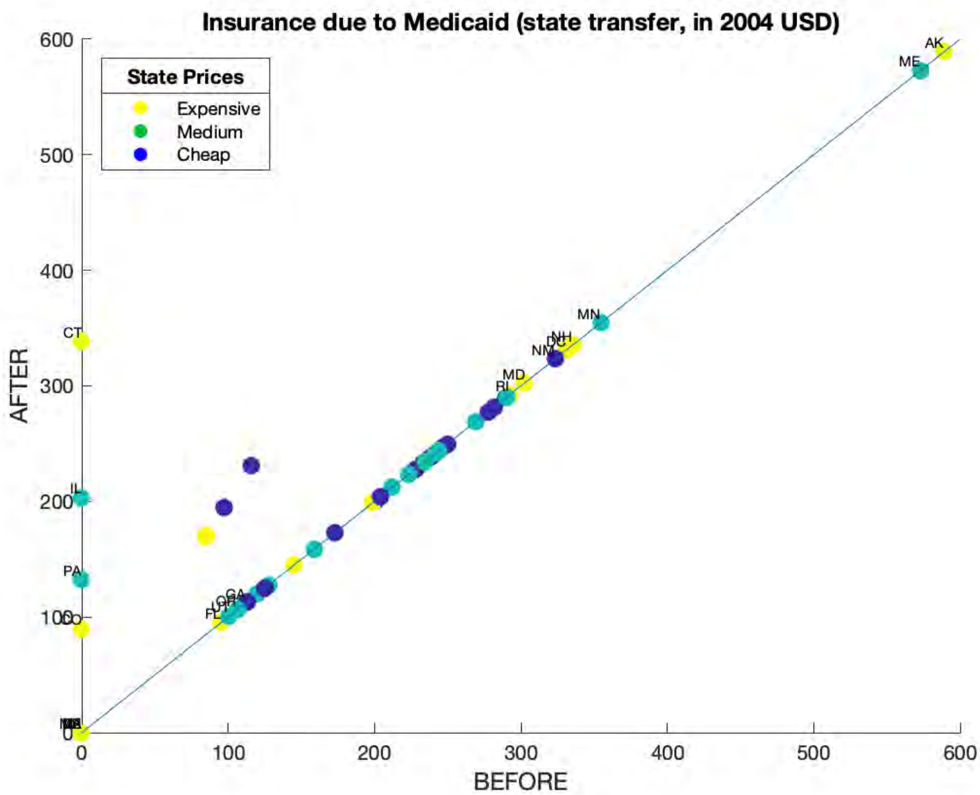

Figure 19: Experiment 2 Medicaid benefits for a negative earnings shock of 10%

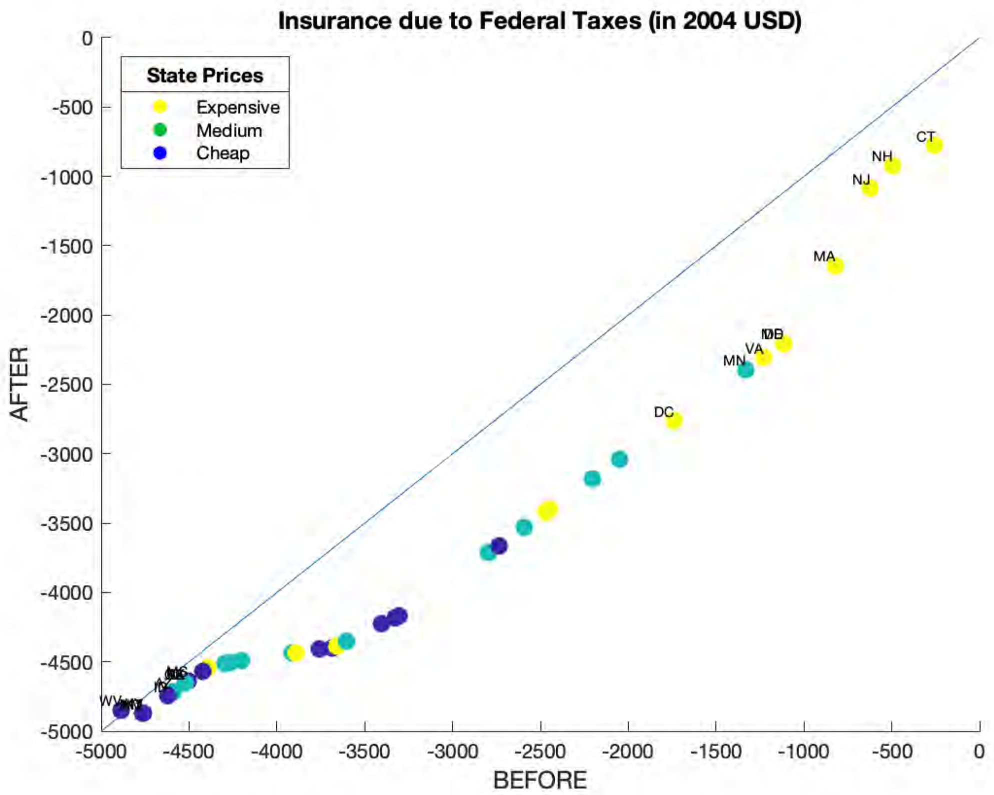

Figure 20: Experiment 2 Federal Income tax/credits for a negative earnings shock of 10%

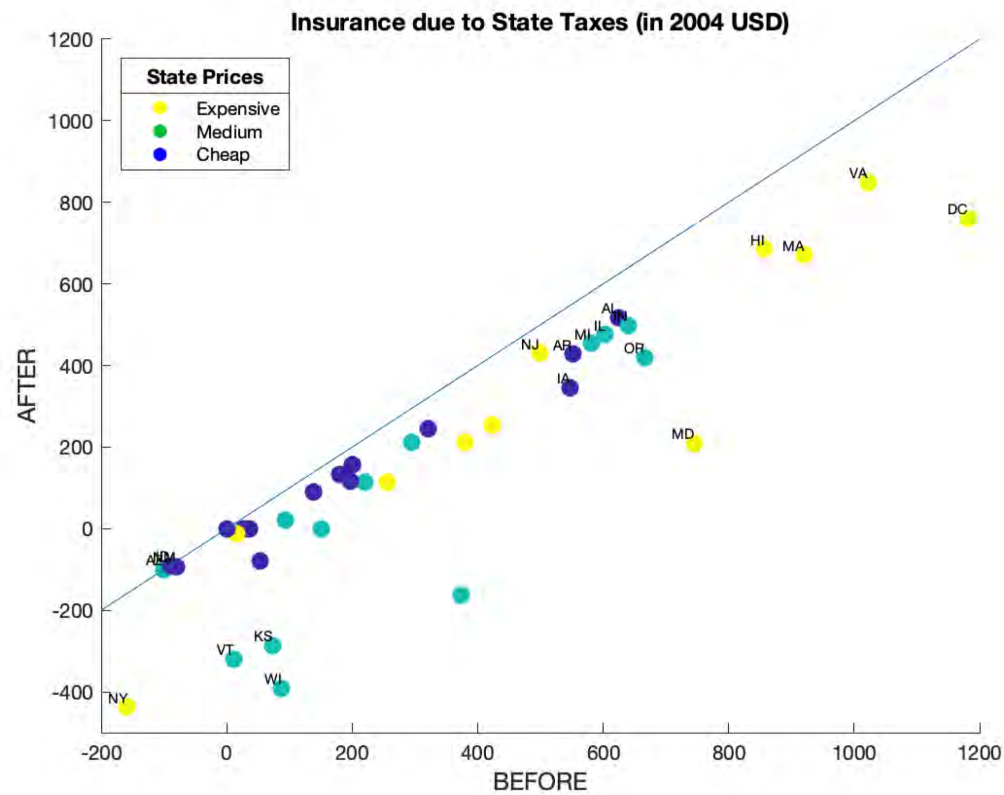

Figure 21: Experiment 2 State income tax/credits for a negative earnings shock of 10%

5 Discussion (Under Revision)

In this section we present some candidate explanations for the patterns of public insurance provision which emerge from our exercise.

Political Preferences We might expect that insurance levels vary because the states, based on their political affiliations, have different preferences over the amount of income reallocation carried out by the government. There are many measures of state political affiliation which we could use, based both on election results and declared preferences through polling. For this exercise we use a measure based on party control of state legislatures, using data on state legislature composition from the National Conference of State Legislatures (NCSL) from 1990 to 2004. We choose to focus on state legislatures rather than presidential elections since state legislatures would be responsible for setting the state level policies [18].

The NCSL measure classifies a state as Democrat in a particular year if, as of January of that year, both the upper and the lower house of the that state's legislature have a majority of Democrat representatives. The state is classified as Split if each party holds one of the chambers. This measure is available every two years from 1990 to 2004 for every state except Nebraska, which has a bipartisan unicameral legislature. We use this to calculate an index of political affiliation as the difference between the number of times a state was classified as Democrat in this period and the number of times it was classified as Republican (Split classifications therefore count as 0). This index therefore ranges from a minimum of -8, for a state like Idaho which was always Republican over this period, to +8, for a state like Alabama which was always Democrat. By this measure most states have had a relatively clear and stable political affiliation, but there are some exceptions like Nevada and New York which have had a Split affiliation in every year.

Figure 22 shows the decomposition of insurance values for Experiment 1 with colour coding to indicate the political affiliation of each state. With the exception of Idaho, the most Republican states seem to operate closer to the frontier in the sense that they achieve a given level of insurance with the highest possible federal contribution. In contrast, the area of the sample which is closer to the origin seems to be dominated by Democrat and Split (Purple) affiliation states. This group of states, which includes Hawaii, Alabama and New York, have unusually high state contributions given the level of insurance which they achieve.

However, there is no obvious relationship between the overall level of insurance and the state's party affiliation.

Differences in Household Composition Another hypothesis is that the composition of households may vary between states. If our prototype household in not very common in a particular state, that state may provide low insurance according to our experiments because its policies are targeting a more prevalent type of household.

The data on household composition do not favour this interpretation. We investigate this by calculating for each state the proportion of residents of voting age who live in a four person household with two children. We report the average of this statistic over the period 2000-2008. With the exceptions of Utah, New Jersey and the District of Columbia, we find that between 3%

[18] We could also have used the party affiliation of the state executive (governor or mayor).

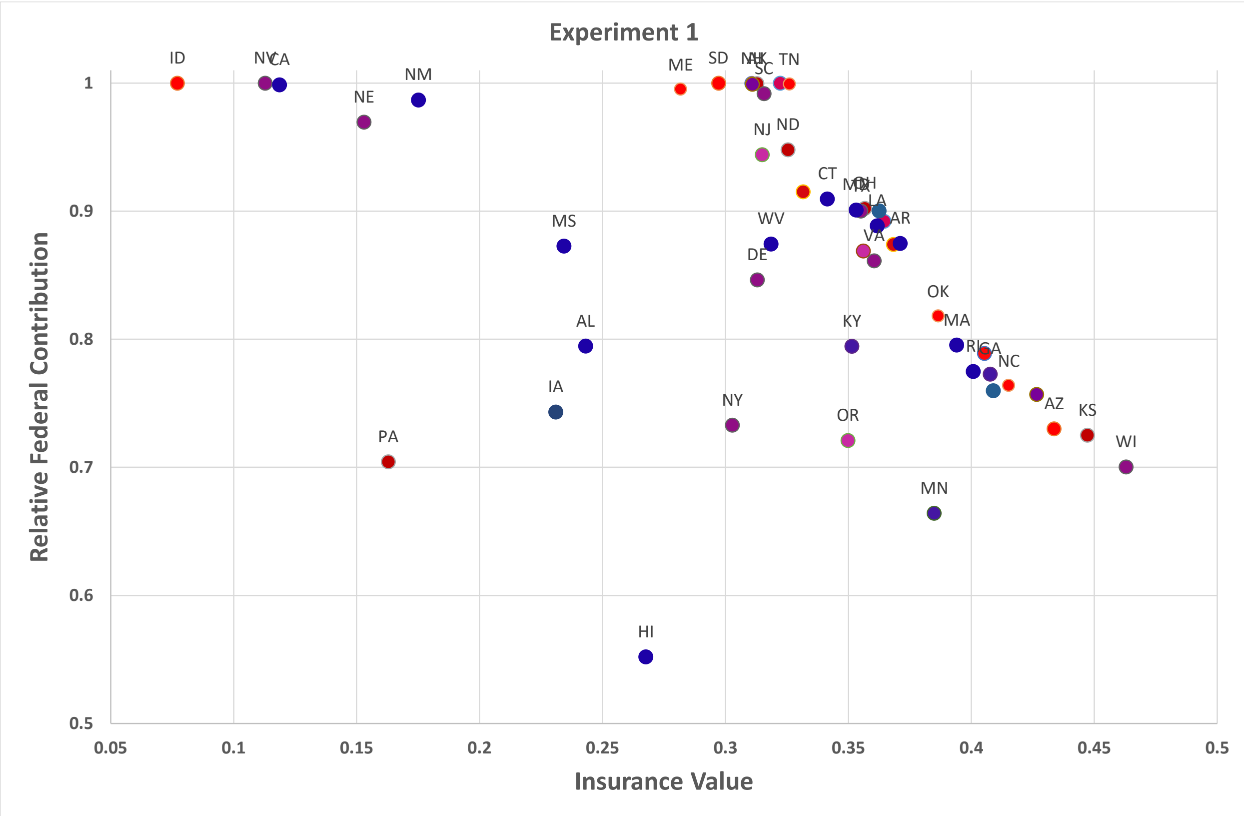

Figure 22: Experiment 1 - Relative contributions with political affiliations based on control of state legislatures. Colour scale: Red- More Republican, Blue-More Democrat, Purple- Split

and 5% of residents in each state live in households with a similar structure to our prototype family.

State Sectoral Compositions
Boar (2018)

Differences in State Level Inequality

6 Concluding Remarks

We present a framework for comparing the level of income insurance received by household in different US states. Against the intuitive benchmark that the federal level of government should aim for uniform insurance to all residents once state policies are accounted for, we find considerable variation between states. In particular, we find that this variation is driven primarily by differences in state fiscal policies. We take this as supporting the claim that differences in state welfare and tax policies determine the level of insurance which a poor household receives in each location.

We interpret these results as demonstrating a limitation on the ability of central fiscal policy to provide uniform income insurance in a federal system. This partly reflects differences in the implementation of state-federal co-financed activities. The results also reflect differences between states in the design of their own welfare programs and tax schedules. Taken together, these variations in local government policies can act as a real constraint on the equalization efforts of the central government. Going forward, we would like to see whether there is any correspondence between the degree of income insurance in each state and the extent to which each state's welfare programs are funded by grants from the federal government.

We would also like to see whether there is a way of accounting for the patterns of insurance provision through differences in the income processes of different states. As documented in Caliendo et al. (2014), the sectoral compositions of the regional economies in the USA are very heterogeneous. It is possible that the resulting exposures to different economic sectors mean that a 'typical' pre-tax income shock is very different from one state to another. The state policies may then be responses to differing levels of income risk. We plan to address this by estimating income processes for a selection of states, using the approach of Storesletten et al. (2004). We would then be able to feed these income processes into our tax and benefit calculators.

References

Albouy, David . The Unequal Geographic Burden of Federal Taxation. *Journal of Political Economy*, 117(4):635–667, August 2009.

Albouy, David . Evaluating the efficiency and equity of federal fiscal equalization. *Journal of Public Economics*, 96(9-10):824–839, oct 2012.

Asdrubali, Pierfederico , Bent Sorensen, and Oved Yosha. Channels of Interstate Risk Sharing: United States 1963-1990. *The Quarterly Journal of Economics*, 111(4):1081–1110, 1996.

Aussenberg, Randy Alison . Supplemental Nutrition Assistance Program (SNAP): A Primer on Eligibility and Benefits. Crs report, Congressional Research Service, 2014.

Austin, Benjamin , Edward Glaeser, and Lawrence Summers. Saving the heartland: Place-based policies in 21st century america. *Brookings Papers on Economic Activity*, 2018.

Autor, David H , David Dorn, and Gordon H Hanson. The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, 103(6): 2121–2168, oct 2013.

Baicker, Katherine , Jeffrey Clemens, and Monica Singhal. The Rise of the States: U.S. Fiscal Decentralization in the Postwar Period. *Journal of Public Economics*, pages 1079–1091, 2010.

Bakija, Jon . Documentation for a Comprehensive Historical U.S. Federal and State Income Tax Calculator Program. Department of economics working papers, Williams College, 2017.

Blanchard, Olivier J. and Lawrence F. Katz. Regional Evolutions. *Brookings Papers on Economic Activity*, 1:1–75, 1992.

Boadway, Robin and Jean-François Tremblay. Reassessment of the Tiebout model. *Journal of Public Economics*, 96(11):1063–1078, 2012.

Boar, Corina . Dynastic precautionary savings. *Working Paper*, 2018.

Bourguignon, François and Amedeo Spadaro. Microsimulation as a tool for evaluating redistribution policies. *The Journal of Economic Inequality*, 4(1):77–106, Apr 2006.

Bronchetti, Erin.T. , Garret Christensen, and Hilary W. Hoynes. Local Food Prices, SNAP Purchasing Power, and Child Health. *Working Paper*, 2017.

Caliendo, Lorenzo , Fernando Parro, Esteban Rossi-Hansberg, and Pierre-Daniel Sarte. The Impact of Regional and Sectoral Productivity Changes on the U.S. Economy. Working Paper 20168, National Bureau of Economic Research, May 2014.

Castner, Laura . Trends in FSP participation rates: focus on 1994 to 1998. Technical report, U.S. Department of Agriculture, Food and Nutrition Service, 2000.

Congressional Budget Office. Effective Marginal Tax Rates for Low- and Moderate-Income Workers. Report 43709, 2012.

Daly, Mary C. and Robert G. Valletta. Cross-national trends in earnings inequality and instability. *Economics Letters*, 99(2):215–219, may 2008.

Dolls, Mathias , Clemens Fuest, and Andreas Peichl. Automatic stabilizers and economic crisis: US vs. Europe. *Journal of Public Economics*, 96(3):279–294, 2012.

Glaeser, Edward L. and Joseph Gyourko. Urban decline and durable housing. *Journal of Political Economy*, 113(2):345–375, 2005.

Glaeser, E.L. . Should transfer payments be indexed to local price levels? *Regional Science and Urban Economics*, 28(1):1–20, jan 1998.

Gordon, Roger H. and Julie Berry Cullen. Income redistribution in a Federal system of governments. *Journal of Public Economics*, 96(11):1100 – 1109, 2012. Fiscal Federalism.

Grant, Charles , Christos Koulovatianos, Alexander Michaelides, and Mario Padula. Evidence on the Insurance Effect of Redistributive Taxation. *The Review of Economics and Statistics*, 92(4): 965–973, November 2010.

Hanson, Kenneth and Margaret Andrews. State Variations in the Food Stamp Benefit Reduction Rate for Earnings - Cross-Program Effects from TANF and SSI Cash Assistance. Economic information bulletin number 46, U.S. Department of Agriculture, Economic Research Service, 2009.

Heathcote, Jonathan , Kjetil Storesletten, and Giovanni L. Violante. Optimal tax progressivity: An analytical framework. *The Quarterly Journal of Economics*, 132(4):1693–1754, 2017.

Hintermaier, Thomas and Winfried Koeniger. Debt portfolios and homestead exemptions. *American Economic Journal: Macroeconomics*, 8(4):103–141, oct 2016.

Holt, Stephen D. and Jennifer L. Romich. Marginal tax rates facing low- and moderate-income workers who participate in means-tested transfer programs. *National Tax Journal*, 60(2):253–276, 2007.

Hoynes, Hilary W. and Erzo F.P. Luttmer. The insurance value of state tax-and-transfer programs. *Journal of Public Economics*, 95(11):1466 – 1484, 2011.

Hoynes, Hilary W. and Diane W. Schanzenbach. *U.S. Food and Nutrition Programs*, pages 219–301. In Moffitt (2016), October 2015.

Hoynes, Hilary W. and James P. Ziliak. Increasing SNAP purchasing power reduces food insecurity and improves child outcomes. Technical report, Brookings Institute, 2018.

Hoynes, Hilary W. , Leslie McGranahan, and Diane W. Schanzenbach. Snap and food consumption. *University of Kentucky Center for Poverty Research Discussion Paper Series, DP2014-03*, 2014.

Inman, Robert P. and Daniel L. Rubinfeld. Designing tax policy in federalist economies: An overview. *Journal of Public Economics*, 60(3):307–334, 1996.

Johnson, Janna E and Morris M Kleiner. Is occupational licensing a barrier to interstate migration? Working Paper 24107, National Bureau of Economic Research, December 2017.

Kaplan, Greg and Sam Schulhofer-Wohl. Understanding The Long-Run Decline In Interstate Migration. *International Economic Review*, 58(1):57–94, feb 2017.

Kaplan, Greg , Giovanni L Violante, and Justin Weidner. The wealthy hand-to-mouth. Working Paper 20073, National Bureau of Economic Research, April 2014.

Kaplow, Louis . Regional cost-of-living adjustments in tax-transfer schemes. Working Paper 5008, National Bureau of Economic Research, February 1995.

Kennan, John and James R. Walker. The effect of expected income on individual migration decisions. *Econometrica*, 79(1):211–251, 2011.

Ladd, Helen F. and Fred C. Doolittle. Which level of government should assist the poor? *National Tax Journal*, 35(3):323–336, 1982.

Maag, Elaine , C.Eugene Steuerle, Ritadhi Chakravarti, and Caleb Quakenbush. How marginal tax rates affect families at various levels of poverty. *National Tax Journal*, 65(4):759–782, December 2012.

Moffitt, Robert A. . *Economics of Means-Tested Transfer Programs in the United States, volume 1*. University of Chicago Press, 2016.

Oates, Wallace . Toward a second-generation theory of fiscal federalism. *International Tax and Public Finance*, 12(4):349–373, 2005.

Oates, Wallace E . An essay on fiscal federalism. *Journal of Economic Literature*, 37(3):1120–1149, sep 1999.

Oliff, Phil , Chris Mai, and Nicholas Johnson. The impact of state income taxes on low-income families in 2011. *Center on Budget and Policy Priorities*, 2012.

Ribar, David C. and Mark O. Wilhelm. The demand for welfare generosity. *The Review of Economics and Statistics*, 81(1):96–108, 1999.

Rodden, Jonathan and Erik Wibbels. Fiscal Decentralization and the Business Cycle: An Empirical Study of Seven Federations. *Economics & Politics*, 22(1):37–67, mar 2010.

Ruggles, Steven , Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek. *Integrated Public Use Microdata Series: Version 7.0*. Minneapolis, MN: University of Minnesota, 2017.

Sommeiller, Estelle and Mark Price. The Increasingly Unequal States of America: Income Inequality by State, 1917 to 2011. *Economic Analysis and Research Network Report*, 2014.

Storesletten, Kjetil , Chris I. Telmer, and Amir Yaron. Cyclical dynamics in idiosyncratic labor market risk. *Journal of Political Economy*, 112(3):695–717, jun 2004.

Tremblay, Antoinette . Longitudinal imputation of sipp food stamp benefits. In *Proceedings of the Survey Research Methods Section, American Statistical Association*, 1994.

Von Hagen, Jürgen . *Fiscal arrangements in a monetary union: evidence from the US*, pages 337–359. Springer Netherlands, Dordrecht, 1992.

Weingast, Barry R. . Second generation fiscal federalism: The implications of fiscal incentives. *Journal of Urban Economics*, 65(3):279–293, may 2009.

Wheaton, Laura and Kathryn Stevens. The effect of different tax calculators on the supplemental poverty measure. Research report, Urban Institute, 2016.

Wilde, Parke . Understanding the food stamp benefit formula. Food assistance and nutrition research report number 14, United States Department of Agriculture, 2001.

Ziliak, James P. . Modernizing snap benefits. *The Hamilton Project*, 2016.

A Appendix

A.1 Welfare Programs

Selected US governmental policies insuring income risk	Expenditures (2007 USD)		Imputation
FEDERAL	total (bn)	recipient/month	
Supplemental Nutrition Assistance Program (SNAP, 'Food Stamps')	30	96	calculator (own brew)
Earned Income Tax Credit (EITC)	49	165	federal tax (TaxSim)
STATE			
Medicaid	329	482	calculator (H. Hoynes)
Temporary Assistance for Needy Families (TANF, formerly AFDC)	12	234	calculator (H. Hoynes)
State Earned Income Tax Credit (SEITC)	NA	NA	state tax (TaxSim)
Unemployment insurance (UI)	*32*	*354*	*(not considered)*

Figure 23: Transfer programs included in simulation

Imputations

A.2 AFDC/TANF and Medicaid

Hoynes and Luttmer (2011) determined eligibility and benefits of the transfer programs "Temporary Assistance for Needy Families" (TANF; "Aid to Families with Dependent Children", AFDC, until 1996) and Medicaid. We use the same calculators and we cordially thank Hilary Hoynes for sharing them with us. The appendix of her paper provides details on the calculators so we just briefly describe their main features.

AFDC/TANF The benefit formula is given as

benefit = maximum benefit - benefit reduction rate × (earnings - earnings disregard) - unearned income

The state specific regulations regarding eligibility and generosity of this program materialize through differences in the earnings disregard, the benefit reduction rate and the maximum benefit. State policy makers enjoyed much less freedom to adjust program parameters prior to the introduction of the AFDC waivers and TANF. For years corresponding to this period the AFDC calculator uses "the most generous tax and disregards for all calculations" while, for years after 1996, the TANF calculator "does not take into account lifetime time limits or work requirements". Finally, the calculators assume a uniform take-up rate of 100%. Regarding the quality of the imputations produced by the calculators, Hoynes and Luttmer (2011) state that their calculations compare favorably with administrative data and other studies (see the appendix of their paper for details).

Medicaid Prior to 1987, eligibility for AFDC leads to mandatory eligibility for Medicaid. To capture the state determined Medicaid expansions in later years, Hoynes and Luttmer (2011) by include state and year specific eligibility parameters for child age and family income thresholds[19]) The benefits are established from administrative data on average expenditures per adult and child by state and year. Regarding take-up rate, the calculator assumes 100% if eligibility

[19] Pregnancy eligibility is also accounted for by the calculator.

arises through AFDC while the take-up rate for eligible children varies by year as given in other sources.

A.3 SNAP (Food Stamps)

Since we could not find a calculator to determine eligibility to the "Supplemental Nutrition Assistance Program" (SNAP, formerly "Food Stamps") and to impute benefits we followed Hoynes and Luttmer (2011) in constructing our own calculator. Our main reference to design its elements was Moffitt (2016), the chapter by Hoynes and Schanzenbach (2015) in particular, as well as the comprehensive summaries and benchmark imputations presented in Hoynes et al. (2014) and Tremblay (1994). We also consulted Aussenberg (2014), Wilde (2001) and Hanson and Andrews (2009) to familiarize ourselves with details on the SNAP definition of net income as presented in section A.3.2 and its interaction with other transfer programs.

A.3.1 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. SNAP regulations define the unit for which eligibility needs to be established as consisting of all household members "who purchase and prepare food together". In concrete terms, any household has to meet three criteria to be considered eligible:

1. Gross monthly income has to be below or equal to 130% of the Federal Poverty Level (FPL).[20]
2. Net income (income after specified deductions, see section A.3.2) has to be below or equal to 100% of the FPL.
3. Countable assets may not exceed a certain amount.

Our calculator accounts for 1 and 2 but does not consider 3. This is because we have not been able to find the asset limits in current nominal US Dollars for the different years and family sizes as well as a comprehensive definitions of countable assets. As mentioned above, there are minor differences across states in this respect.

A.3.2 Benefits

Following the information provided in our references, the SNAP benefit formula is given as

SNAP benefit = maximum benefit − benefit reduction rate × *net income*

[20] While the term FPL is used frequently, this measure actually refers to the 'Poverty Guidelines' (PG). They 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 which accounts for the higher cost of living in these two states.

Maximum Benefit We capture maximum benefits by making use of the fact the SNAP is designed to cover monthly food expenditures of families with different sizes as established by the Thrifty Food Plan (TFP)[21]. Hence, to obtain the maximum benefit data for various family sizes and years, we collected data on the current US Dollar amounts corresponding to the TFP.[22] As this information is not available in a consolidated database for the years we study, we combined information from several sources for different time periods:

- **1976 to 1995** We use data provided by Castner (2000) (Table B3). Note that current US Dollar amounts are only available for even years until 1990. For uneven years before, we use the average value of the preceding and following year.
- **1996 to 2003** We use data information from the "Supplemental Nutrition Assistance Program Quality Control Data". They are included in the quality control reports published by the U.S. Department of Agriculture's (USDA) Food and Consumer Service (FCS), which is administering SNAP (and already administered the program when it was called Food Stamp Program).[23]
- **from 2004** We use data from the Cost of Living Adjustment (COLA) database. The data are provided by the USDA's Food and Nutrition Service.[24]

As a consistency check, we compare the values from the different sources for years in which they overlap. We find that between 1990 and 2000, the data from Castner (2000) and the USDA are identical, while from 2000 to 2005, the USDA and COLA data are the same. Hence, we have confidence that the maximum benefits are correctly specified in our calculator.

Net Income 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)

As our prototype household does not meet the criteria captured in (4), (5) and (6), our calculator does not consider them. For (2), we could not find the data for different years and family

[21]"Benefits are tied to the cost of a âĂIJmarket basked of foods which if prepared and consumed at home, would provide a complete, nutritious diet at minimal costâĂİ, the so-called Thrifty Food Plan, (...)." Moffitt (2016), page 226. The Thrifty Food Plan (TFP) measures the average monthly cost of a healthy meal plan for different family sizes. It is computed by the US Department of Agriculture and a key policy measure in setting nutritional cost standards.

[22]Note that Congress can choose to increase maximum benefits above the TFP level during economic downturns. For example, this was one element of the American Recovery and Reinvestment Act of 2009. Our calculator accounts for this temporary policy change.

[23]Mathematica Policy Research was contracted to produce the reports and datasets. Both are available at https://host76.mathematica-mpr.com/fns/ See appendix C of the technical documentation for program parameters such as the maximum benefit, income screen etc.

[24]See https://www.fns.usda.gov/snap/cost-living-adjustment-cola-information

sizes so we omit this deduction. However, the calculator 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 include include cash transfers. While disbursements of social security, disability income and unemployment insurance would meet this criterion, they are not relevant due to the specification of our prototype household. What matters for our household are AFDC/TANF transfers which our SNAP calculator adds to cash pre-tax income.

Benefit Reduction Rate While the official SNAP benefit reduction rate is 0.3, Hoynes and Schanzenbach (2015) argue that the rate which applies in practice is below this statutory value because of the deductions to net income described above. Another source of variation of the benefit reduction rate is described in Hanson and Andrews (2009). They show that, from a household perspective, the SNAP benefit reduction rate is subject to interaction with other welfare programs such as AFDC/TANF. As the benefits of these programs vary by state and year, the SNAP benefit reduction rate is likely to vary across states and years as well. To account for this issue, we simulate our model with two different benefit reduction rates (0.3 and 0.15). However, our results are robust as the quantitative changes induced by this variation are minor. This is because eligibility is not affected by the benefit reduction rate (see section A.3.1) and because those households which receive SNAP benefits have very low values of net income.

A.3.3 Take-up rates

The USDA publishes annual reports titled "Estimates of State Supplemental Nutrition Assistance Program Participation Rates". These reports document that participation rates vary considerably across states and years. It has been pointed out that these differences are partly associated with asymmetric state business cycle movements and other state and local policies such as school lunch and emergency food programs. Moreover, participation rates also depend on the amounts of collectable benefits. As we are interested to study a household which is comparable across years and states (our prototype family), we do not account for differences in take up rates in our SNAP calculator. On the one hand, this is because we aim to measure the maximum amount of transfers available to households and not those actually collected. On the other hand, we do not want to capture outcomes which are plausibly linked to specific state (and year) effects to keep our results focused on comparability.

A.4 Taxes

We use TaxSim to obtain federal and state liabilities for different years and states. TaxSim provides federal taxes since 1960 and state taxes since 1977. Importantly, it includes state and federal earned income tax credits and accounts for different state rules on deductibility of federal taxes as well as child care tax credits. Moreover, it allows to account for household characteristics such as number of children which are relevant determinants of a family's actual total tax burden. We use the income data we obtained from the data (see above) corresponding to poor and rich families in the different years and states. Moreover, we account for transfer incomes imputed by our calculators described above, i.e. we make sure to use the best estimate for taxable income.

How accurate are our federal and state tax imputations? We first note that TaxSim is the almost exclusive tool used for this purpose so our imputations are no worse than those of the vast majority of other contributions. Second, since we cannot observe the tax data we are interested in (see above discussion), we have to rely on imputation. Hence, the only benchmark for comparison are alternative tax calculators. To the best of our knowledge, there are two other candidates: The tax calculator developed and maintained by Bakija (2017) and the Urban Institute's Transfer Income Model (TRIM).[25] To judge if any of these alternatives is strictly superior to TaxSim for the purpose of our project, we present below a succinct summary of Wheaton and Stevens (2016) who conduct a detailed comparison of all three tax calculators.

Federal Taxes For federal income taxes (table 2A), there are only negligible differences between the three tax calculators. All three are either equally close to or far from the target defined by administrative tax data. Differences between them are always in the ballpark of two to three percentage points.[26] This impression is confirmed by the more detailed comparisons presented in table 2B and applies even more to tax credits (table 2C) where the three alternatives produce virtually identical results.

State Taxes Regarding state income taxes (tables A4 and 4B) TRIM performs consistently worse than TaxSim and Bakija. While they are close in terms of meeting the target, it appears that TaxSim is marginally superior. For state earned income tax credits, all three are lining up closely but TaxSim seems again a marginal winner based on the summary evaluation presented in the final rows of table 4C.

As Wheaton and Stevens (2016) demonstrate the relative performance of the three tax calculators also depends on the source of the tax variables. However even for different inputs (Census or TRIM tax variables), the variation between them remains minor. Since we are using our own input variables – which are different from the ones used by Wheaton and Stevens (2016) – we conclude that conditional on our inputs the variation across the different calculators is likely to be small and that TaxSim is overall the best choice for our project. Therefore, we think the imputation procedure of federal and state taxes is the best we can achieve as we have no reason to believe that any of the other tools would give more accurate results.

A.5 Data inputs

As inputs to our simulation model, we obtain data on households in different years and states from the Integrated Public Use Microdata Series (IPUMS, Ruggles et al. (2017)) USA dataset. It provides cross-sectional variables on households in different states and years (dating back as early as 1850). Since we only have state taxes since 1977, we choose 1980 as the first year of our analysis. IPUMS assembles information from several sources, such as the decennial censuses (for years 1980 and 1990) and the American Community Survey (ACS; annual since 2000). Importantly, variable codes and labels are harmonized across years and data sources so that they consistently contain the same information.

[25] See here http://trim.urban.org/T3Welcome.php

[26] The only exception is the alternative minimum tax where TRIM performs better than TaxSim and Bakija by eight and five percentage points respectively.

A.5.1 Household Income

We use total annual family income[27] as the income variable of households and classify households as poor or rich based on the 10% and 90% percentiles of the corresponding state and year distributions. This measure for income comprises current USD amounts of annual "total pre-tax money income earned by one's family from all sources". Since this variable sums the incomes of all family members who are related to the head it excludes incomes of family members who are not related to the head. To check if this aspect makes a quantitative difference, we also use a personal income variable[28] which "reports income earned from wages or a person's own business or farm for the previous year" and sum it for all family members (related to the head or not) by using the family relationship variables. The results are virtually identical.

[27] IPUMS variable is "FTOTINC"

[28] "INCEARN"

B Complete Results of Main Experiments

The tables for the state and federal government decompositions of the two experiments in the text of the paper are presented in the next pages in the following order:

1. Experiment 1: Federal insurance against negative shocks
2. Experiment 1: Federal insurance against positive shocks
3. Experiment 1: State insurance against negative shocks
4. Experiment 1: State insurance against positive shocks
5. Experiment 2: Federal insurance against positive and negative shocks
6. Experiment 2: State insurance against positive and negative shocks

	-0.5	-1	-1.5	-2	-2.5	-3	-3.5	-4	-4.5	-5
Alabama	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Alaska	0.0771	0.0773	0.0772	0.0773	0.0772	0.0773	0.0772	0.0773	0.0772	0.0773
Arizona	0.2785	0.2531	0.2442	0.2212	0.1925	0.1732	0.1595	0.1493	0.1412	0.1349
Arkansas	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
California	0.3095	0.3102	0.3104	0.3105	0.3105	0.3106	0.3104	0.3105	0.3105	0.3114
Colorado	0.0772	0.0774	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Connecticut	0.3265	0.3273	0.3271	0.3153	0.2978	0.2860	0.2646	0.2411	0.2229	0.2084
Delaware	0.3263	0.3271	0.3128	0.2915	0.2786	0.2570	0.2314	0.2121	0.1971	0.1851
District of Columbia	0.3107	0.3107	0.3107	0.3107	0.3107	0.3107	0.3107	0.3107	0.3126	0.3140
Florida	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Georgia	0.0774	0.0774	0.0774	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Hawaii	0.3108	0.3108	0.3108	0.3104	0.3105	0.3106	0.3106	0.3106	0.3106	0.3106
Idaho	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0772	0.0772	0.0772	0.0772
Illinois	0.0772	0.0774	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Indiana	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Iowa	0.0771	0.0773	0.0772	0.0773	0.0773	0.0772	0.0773	0.0773	0.0773	0.0773
Kansas	0.0770	0.0772	0.0773	0.0772	0.0772	0.0773	0.0772	0.0772	0.0773	0.0773
Kentucky	0.0772	0.0774	0.0774	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Louisiana	0.0773	0.0773	0.0773	0.0773	0.0772	0.0772	0.0772	0.0773	0.0773	0.0773
Maine	0.0771	0.0771	0.0772	0.0772	0.0773	0.0772	0.0772	0.0773	0.0772	0.0772
Maryland	0.0773	0.0773	0.0773	0.0774	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Massachusetts	0.0771	0.0772	0.0773	0.0772	0.0773	0.0772	0.0773	0.0773	0.0773	0.0773
Michigan	0.0774	0.0772	0.0773	0.0772	0.0773	0.0772	0.0773	0.0773	0.0773	0.0773
Minnesota	0.0775	0.0773	0.0772	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Mississippi	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Missouri	0.0772	0.0774	0.0773	0.0773	0.0772	0.0773	0.0773	0.0773	0.0773	0.0773
Montana	0.1061	0.0917	0.0868	0.0845	0.0831	0.0821	0.0814	0.0809	0.0805	0.0802
Nebraska	0.0772	0.0772	0.0772	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Nevada	0.3102	0.3102	0.3107	0.3143	0.3168	0.3187	0.3199	0.3208	0.3214	0.3221
New Hampshire	0.2274	0.2274	0.2204	0.1846	0.1631	0.1488	0.1386	0.1310	0.1250	0.1202
New Jersey	0.3278	0.3279	0.3273	0.3275	0.3272	0.3273	0.3191	0.3076	0.2987	0.2787
New Mexico	0.0775	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
New York	0.3119	0.3112	0.3157	0.3186	0.3203	0.3214	0.3222	0.3228	0.3233	0.3152
North Carolina	0.0773	0.0773	0.0772	0.0772	0.0772	0.0773	0.0773	0.0773	0.0773	0.0772
North Dakota	0.0771	0.0771	0.0773	0.0772	0.0772	0.0773	0.0773	0.0772	0.0773	0.0773
Ohio	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Oklahoma	0.0775	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Oregon	0.3099	0.3106	0.3127	0.3166	0.3186	0.3201	0.3210	0.3219	0.3224	0.3183
Pennsylvania	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Rhode Island	0.2417	0.2341	0.2319	0.1988	0.1745	0.1583	0.1467	0.1380	0.1313	0.1259
South Carolina	0.0774	0.0774	0.0772	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
South Dakota	0.0771	0.0772	0.0772	0.0772	0.0773	0.0772	0.0773	0.0773	0.0772	0.0773
Tennessee	0.0771	0.0771	0.0773	0.0772	0.0772	0.0773	0.0773	0.0772	0.0773	0.0773
Texas	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Utah	0.0771	0.0773	0.0772	0.0773	0.0772	0.0773	0.0772	0.0773	0.0772	0.0773
Vermont	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Virginia	0.3268	0.3166	0.2867	0.2718	0.2544	0.2249	0.2038	0.1879	0.1757	0.1658
Washington	0.3248	0.3263	0.3263	0.3267	0.3269	0.3268	0.3269	0.3185	0.3083	0.3002
West Virginia	0.0772	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Wisconsin	0.2270	0.1928	0.1543	0.1350	0.1235	0.1158	0.1103	0.1061	0.1029	0.1004
Wyoming	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0772	0.0772	0.0772

	5	4.5	4	3.5	3	2.5	2	1.5	1	0.5
Alabama	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Alaska	0.1633	0.1452	0.1297	0.1159	0.0972	0.0773	0.0773	0.0773	0.0773	0.0775
Arizona	0.3232	0.3245	0.3262	0.3273	0.3272	0.3271	0.3274	0.3272	0.3270	0.3278
Arkansas	0.0891	0.0772	0.0772	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
California	0.2182	0.2314	0.2478	0.2689	0.2971	0.3108	0.3108	0.3108	0.3108	0.3108
Colorado	0.2572	0.2495	0.2398	0.2274	0.2105	0.1872	0.1706	0.1519	0.1137	0.0772
Connecticut	0.3176	0.3183	0.3193	0.3204	0.3222	0.3247	0.3274	0.3276	0.3274	0.3282
Delaware	0.3193	0.3204	0.3215	0.3232	0.3252	0.3273	0.3275	0.3274	0.3279	0.3279
District of Columbia	0.2571	0.2746	0.2964	0.3105	0.3105	0.3104	0.3107	0.3107	0.3107	0.3107
Florida	0.2850	0.2802	0.2744	0.2668	0.2567	0.2426	0.2215	0.2061	0.1955	0.1636
Georgia	0.1656	0.1476	0.1314	0.1176	0.0995	0.0772	0.0772	0.0773	0.0772	0.0770
Hawaii	0.1804	0.1893	0.2004	0.2148	0.2339	0.2607	0.3008	0.3108	0.3108	0.3108
Idaho	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Illinois	0.2562	0.2483	0.2385	0.2258	0.2086	0.1849	0.1689	0.1495	0.1107	0.0772
Indiana	0.1326	0.1204	0.1071	0.0900	0.0773	0.0773	0.0772	0.0772	0.0771	0.0773
Iowa	0.0773	0.0773	0.0773	0.0773	0.0772	0.0773	0.0773	0.0772	0.0773	0.0771
Kansas	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0774	0.0774
Kentucky	0.0773	0.0773	0.0773	0.0773	0.0772	0.0772	0.0772	0.0772	0.0772	0.0772
Louisiana	0.0773	0.0773	0.0772	0.0772	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Maine	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0774	0.0773	0.0775
Maryland	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0772	0.0772
Massachusetts	0.1977	0.1834	0.1653	0.1447	0.1310	0.1117	0.0830	0.0773	0.0772	0.0774
Michigan	0.1754	0.1585	0.1387	0.1260	0.1090	0.0855	0.0772	0.0773	0.0772	0.0774
Minnesota	0.0773	0.0773	0.0772	0.0773	0.0772	0.0773	0.0773	0.0772	0.0773	0.0771
Mississippi	0.1895	0.1741	0.1550	0.1378	0.1230	0.1021	0.0772	0.0772	0.0771	0.0770
Missouri	0.1828	0.1668	0.1468	0.1324	0.1164	0.0943	0.0773	0.0773	0.0772	0.0772
Montana	0.2978	0.2946	0.2904	0.2853	0.2782	0.2683	0.2538	0.2290	0.2277	0.2277
Nebraska	0.0772	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0772	0.0772	0.0772
Nevada	0.3106	0.3107	0.3106	0.3106	0.3107	0.3105	0.3106	0.3107	0.3109	0.3102
New Hampshire	0.3229	0.3242	0.3253	0.3250	0.3246	0.3243	0.3236	0.3223	0.3196	0.3118
New Jersey	0.3121	0.3122	0.3125	0.3127	0.3130	0.3136	0.3142	0.3152	0.3180	0.3249
New Mexico	0.1741	0.1572	0.1377	0.1250	0.1078	0.0840	0.0772	0.0772	0.0773	0.0771
New York	0.3105	0.3105	0.3105	0.3105	0.3105	0.3105	0.3105	0.3105	0.3105	0.3104
North Carolina	0.2638	0.2567	0.2478	0.2365	0.2213	0.2004	0.1803	0.1645	0.1331	0.0773
North Dakota	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0776
Ohio	0.2438	0.2345	0.2228	0.2079	0.1880	0.1659	0.1506	0.1250	0.0771	0.0773
Oklahoma	0.2782	0.2726	0.2658	0.2572	0.2456	0.2290	0.2045	0.1929	0.1753	0.1237
Oregon	0.3106	0.3107	0.3106	0.3107	0.3106	0.3107	0.3106	0.3108	0.3106	0.3113
Pennsylvania	0.0772	0.0773	0.0773	0.0773	0.0773	0.0772	0.0772	0.0772	0.0773	0.0773
Rhode Island	0.3239	0.3253	0.3271	0.3273	0.3272	0.3271	0.3274	0.3273	0.3270	0.3278
South Carolina	0.2923	0.2883	0.2836	0.2773	0.2689	0.2572	0.2400	0.2205	0.2169	0.2063
South Dakota	0.1531	0.1340	0.1222	0.1073	0.0873	0.0773	0.0773	0.0773	0.0774	0.0774
Tennessee	0.1839	0.1678	0.1479	0.1331	0.1173	0.0954	0.0773	0.0773	0.0773	0.0775
Texas	0.2926	0.2889	0.2841	0.2779	0.2696	0.2583	0.2410	0.2213	0.2182	0.2088
Utah	0.2805	0.2752	0.2689	0.2604	0.2494	0.2337	0.2105	0.1973	0.1827	0.1375
Vermont	0.1109	0.0979	0.0818	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
Virginia	0.3208	0.3218	0.3233	0.3251	0.3274	0.3271	0.3272	0.3274	0.3268	0.3268
Washington	0.3107	0.3106	0.3108	0.3107	0.3106	0.3108	0.3108	0.3106	0.3111	0.3111
West Virginia	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0772	0.0772	0.0772	0.0772
Wisconsin	0.3116	0.3102	0.3081	0.3054	0.3018	0.2965	0.2889	0.2762	0.2508	0.2282
Wyoming	0.2442	0.2349	0.2234	0.2085	0.1887	0.1665	0.1513	0.1259	0.0773	0.0773

	-0.5	-1	-1.5	-2	-2.5	-3	-3.5	-4	-4.5	-5
Alabama	0.0400	0.0400	0.0400	0.0400	0.0400	0.0400	0.0400	0.0400	0.0400	0.0400
Alaska	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Arizona	0.0000	0.1339	0.0893	0.0670	0.0536	0.0446	0.0383	0.0335	0.0698	0.0628
Arkansas	0.0360	0.0360	0.0361	0.0361	0.0361	0.0361	0.0361	0.0361	0.0361	0.0361
California	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0221	0.0197	0.0177
Colorado	0.0000	0.0000	0.0000	0.0000	0.0518	0.0432	0.0370	0.0324	0.0288	0.0259
Connecticut	0.0060	0.0055	0.0050	0.0045	0.0040	0.0035	0.0030	0.0027	0.0024	0.0021
Delaware	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
District of Columbia	0.1277	0.1277	0.1277	0.1277	0.1277	0.1277	0.1263	0.1233	0.1210	0.1192
Florida	0.0000	0.0000	0.0000	0.0000	0.0000	0.0452	0.0388	0.0339	0.0301	0.0271
Georgia	0.0301	0.2002	0.1435	0.1151	0.0981	0.0867	0.0773	0.0796	0.0730	0.0677
Hawaii	0.0680	0.0680	0.0680	0.0680	0.0680	0.0673	0.0669	0.0665	0.0662	0.0660
Idaho	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Illinois	0.0405	0.0406	0.0406	0.0406	0.0405	0.0405	0.0405	0.0405	0.0406	0.0405
Indiana	0.0467	0.0467	0.0467	0.0467	0.0466	0.0466	0.0466	0.0466	0.0466	0.0467
Iowa	0.0585	0.0587	0.0587	0.0546	0.0437	0.0364	0.0312	0.0273	0.0243	0.0219
Kansas	0.0663	0.0665	0.0666	0.0665	0.0666	0.0666	0.0665	0.0666	0.0666	0.0666
Kentucky	0.0570	0.1345	0.1045	0.0890	0.0797	0.0735	0.0691	0.0657	0.0631	0.0611
Louisiana	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200
Maine	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maryland	0.0896	0.0896	0.0896	0.0898	0.0897	0.0893	0.0883	0.0875	0.0868	0.0853
Massachusetts	0.0803	0.0805	0.0806	0.0805	0.0805	0.0805	0.0805	0.0805	0.0805	0.0805
Michigan	0.0663	0.0661	0.0661	0.0661	0.0661	0.0661	0.0661	0.0661	0.0661	0.0661
Minnesota	0.0222	0.0111	0.0074	0.0055	0.0044	0.0037	0.0032	-0.0119	-0.0327	-0.0494
Mississippi	0.0300	0.1760	0.1273	0.1030	0.0870	0.0725	0.0622	0.0544	0.0483	0.0435
Missouri	0.0250	0.0250	0.0250	0.0242	0.0233	0.0228	0.0224	0.0221	0.0219	0.0214
Montana	0.0240	0.0240	0.0240	0.0240	0.0240	0.0891	0.0798	0.0729	0.0674	0.0631
Nebraska	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Nevada	0.1952	0.0976	0.0651	0.0488	0.0390	0.0325	0.0279	0.0244	0.0217	0.0195
New Hampshire	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
New Jersey	0.0175	0.0175	0.0175	0.0168	0.0163	0.0159	0.0156	0.0154	0.0153	0.0151
New Mexico	0.0000	0.0628	0.0452	0.0364	0.0311	0.0276	0.0251	0.0232	0.0217	0.0206
New York	0.1036	0.1034	0.1033	0.1033	0.1032	0.1032	0.1032	0.1032	0.1032	0.1032
North Carolina	0.0252	0.0126	0.0084	0.0063	0.0784	0.0653	0.0560	0.0490	0.0436	0.0392
North Dakota	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Ohio	0.0297	0.0297	0.0297	0.0297	0.0297	0.0292	0.0284	0.0279	0.0274	0.0270
Oklahoma	0.0708	0.0706	0.0705	0.0706	0.0706	0.0693	0.0680	0.0671	0.0664	0.0658
Oregon	0.3468	0.2238	0.1826	0.1622	0.1498	0.1416	0.1357	0.1313	0.1279	0.1252
Pennsylvania	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rhode Island	0.0045	0.0045	0.0045	0.0045	0.0042	0.0040	0.0038	0.0036	0.0035	0.0034
South Carolina	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
South Dakota	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Tennessee	0.0000	0.1736	0.1157	0.0868	0.0694	0.0579	0.0496	0.0434	0.0386	0.0347
Texas	0.0000	0.0000	0.0000	0.0000	0.0000	0.0553	0.0474	0.0415	0.0368	0.0332
Utah	0.0329	0.0330	0.0308	0.0288	0.0277	0.0746	0.0673	0.0596	0.0530	0.0477
Vermont	0.0674	0.0674	0.0674	0.0674	0.0674	0.0674	0.0674	0.0674	0.0674	0.1184
Virginia	0.0499	0.0501	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500
Washington	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
West Virginia	0.0300	0.0300	0.0300	0.0300	0.0300	0.0300	0.0300	0.0300	0.0300	0.0300
Wisconsin	0.1305	0.1174	0.1084	0.1039	0.1013	0.0995	0.0982	0.0973	0.0965	0.0960
Wyoming	0.0000	0.0000	0.0000	0.0909	0.0727	0.0606	0.0520	0.0455	0.0404	0.0364

	5	4.5	4	3.5	3	2.5	2	1.5	1	0.5
Alabama	0.0471	0.0467	0.0463	0.0458	0.0451	0.0441	0.0427	0.0402	0.0400	0.0400
Alaska	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Arizona	0.0601	0.0636	0.0680	0.0736	0.0811	0.0000	0.0000	0.0000	0.0000	0.0000
Arkansas	0.0437	0.0434	0.0431	0.0426	0.0420	0.0412	0.0399	0.0377	0.0361	0.0361
California	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Colorado	0.0244	0.0219	0.0189	0.0150	0.0098	0.0025	0.0000	0.0000	0.0000	0.0000
Connecticut	0.0128	0.0111	0.0104	0.0099	0.0094	0.0089	0.0084	0.0079	0.0074	0.0070
Delaware	0.0739	0.0768	0.0341	0.0322	0.0295	0.0258	0.0203	0.0110	0.0000	0.0000
District of Columbia	0.1143	0.1186	0.1241	0.1276	0.1276	0.1276	0.1277	0.1277	0.1277	0.1277
Florida	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Georgia	0.0439	0.0432	0.0424	0.0413	0.0400	0.0400	0.0400	0.0400	0.0400	0.0398
Hawaii	0.0680	0.0680	0.0680	0.0680	0.0680	0.0680	0.0680	0.0680	0.0680	0.0680
Idaho	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Illinois	0.0405	0.0405	0.0405	0.0405	0.0405	0.0405	0.0405	0.0405	0.0405	0.0405
Indiana	0.0466	0.0466	0.0466	0.0466	0.0466	0.0466	0.0466	0.0466	0.0465	0.0467
Iowa	0.0587	0.0587	0.0587	0.0587	0.0587	0.0587	0.0587	0.0587	0.0587	0.0585
Kansas	0.1058	0.1101	0.1156	0.1226	0.1319	0.1450	0.0666	0.0666	0.0667	0.0667
Kentucky	0.0570	0.0570	0.0570	0.0570	0.0570	0.0570	0.0570	0.0570	0.0570	0.0570
Louisiana	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200
Maine	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maryland	0.0831	0.0831	0.0832	0.0833	0.0835	0.0836	0.0839	0.0844	0.0854	0.0883
Massachusetts	0.0805	0.0806	0.0806	0.0805	0.0806	0.0805	0.0806	0.0806	0.0805	0.0807
Michigan	0.0535	0.0550	0.0570	0.0594	0.0628	0.0661	0.0661	0.0661	0.0661	0.0663
Minnesota	0.1030	0.1030	0.1030	0.1030	0.1029	0.1030	0.1030	0.1029	0.1030	0.1027
Mississippi	0.0300	0.0300	0.0300	0.0300	0.0300	0.0300	0.0300	0.0300	0.0299	0.0298
Missouri	0.0293	0.0287	0.0283	0.0281	0.0278	0.0273	0.0267	0.0256	0.0250	0.0250
Montana	0.0281	0.0280	0.0280	0.0280	0.0280	0.0280	0.0280	0.0280	0.0281	0.0280
Nebraska	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Nevada	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
New Hampshire	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
New Jersey	0.0720	0.0780	0.0856	0.0953	0.1083	0.1265	0.1537	0.0175	0.0175	0.0174
New Mexico	0.0031	0.0016	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
New York	0.1369	0.1407	0.1454	0.1514	0.1595	0.1707	0.1876	0.2158	0.2722	0.4412
North Carolina	0.0600	0.0600	0.0600	0.0600	0.0600	0.0600	0.0600	0.0600	0.0600	0.0600
North Dakota	0.0382	0.0425	0.0478	0.0546	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Ohio	0.0303	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297	0.0298
Oklahoma	0.0705	0.0705	0.0705	0.0705	0.0705	0.0705	0.0705	0.0705	0.0704	0.0704
Oregon	0.1005	0.1006	0.1005	0.1006	0.1005	0.1006	0.1005	0.1006	0.1005	0.1008
Pennsylvania	0.0451	0.0501	0.0564	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rhode Island	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045
South Carolina	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
South Dakota	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Tennessee	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Texas	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Utah	0.0422	0.0411	0.0398	0.0387	0.0382	0.0374	0.0363	0.0343	0.0331	0.0331
Vermont	0.0674	0.0674	0.0674	0.0674	0.0674	0.0674	0.0674	0.0674	0.0674	0.0674
Virginia	0.1042	0.1102	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0499	0.0499
Washington	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
West Virginia	0.0738	0.0379	0.0376	0.0373	0.0368	0.0362	0.0352	0.0336	0.0304	0.0300
Wisconsin	0.1348	0.1331	0.1321	0.1315	0.1308	0.1307	0.1307	0.1308	0.1309	0.1312
Wyoming	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

	-0.2	-0.15	-0.1	-0.05	0.05	0.1	0.15	0.2
Alabama	0.1944	0.2381	0.1349	0.1135	0.1679	0.1886	0.1987	0.2597
Alaska	0.3179	0.3199	0.2756	0.3160	0.0869	0.3234	0.2776	0.2400
Arizona	0.2066	0.2746	0.1326	0.0891	0.2067	0.2662	0.2581	0.2757
Arkansas	0.1273	0.1453	0.1309	0.2761	0.0656	0.0732	0.0877	0.2206
California	0.2753	0.2737	0.1393	0.1858	0.1667	0.2242	0.2087	0.2485
Colorado	0.2687	0.3025	0.2053	0.3047	0.3074	0.3148	0.3088	0.3161
Connecticut	0.1517	0.1578	0.1438	0.1466	0.1753	0.1493	0.1647	0.1765
Delaware	0.2548	0.1875	0.2369	0.2221	0.2835	0.2494	0.2965	0.3181
District of Columbia	0.2853	0.3167	0.1846	0.2717	0.3140	0.2928	0.3104	0.2611
Florida	0.2642	0.2733	0.1300	0.2227	0.2407	0.2776	0.2645	0.2740
Georgia	0.3127	0.3155	0.1663	0.2232	0.2903	0.2930	0.2888	0.2990
Hawaii	0.3119	0.2995	0.1698	0.2783	0.1926	0.1771	0.3109	0.3209
Idaho	0.2106	0.1259	0.1098	0.0798	0.1639	0.1217	0.1027	0.2734
Illinois	0.2468	0.2763	0.2684	0.2969	0.3193	0.2973	0.3112	0.3192
Indiana	0.2953	0.3176	0.2080	0.3132	0.2904	0.3199	0.3088	0.3188
Iowa	0.2840	0.3105	0.2204	0.2985	0.3141	0.3111	0.3108	0.3162
Kansas	0.3124	0.3079	0.1894	0.2813	0.2754	0.3064	0.2931	0.3119
Kentucky	0.1273	0.1284	0.1273	0.0707	0.0985	0.1845	0.1637	0.2187
Louisiana	0.2254	0.1532	0.1273	0.1081	0.1871	0.1845	0.2020	0.3060
Maine	0.3138	0.3206	0.1524	0.2211	0.2023	0.1605	0.1617	0.2983
Maryland	0.2057	0.2326	0.2567	0.2252	0.1708	0.1543	0.1709	0.1922
Massachusetts	0.1601	0.1633	0.1641	0.1870	0.2063	0.1910	0.1786	0.2129
Michigan	0.2897	0.3045	0.2679	0.2895	0.3053	0.3150	0.2964	0.2980
Minnesota	0.2021	0.2001	0.1980	0.2425	0.3043	0.2673	0.2420	0.2964
Mississippi	0.2308	0.2099	0.1364	0.1228	0.0961	0.1528	0.1378	0.2447
Missouri	0.3154	0.3182	0.2080	0.2552	0.1958	0.2369	0.2235	0.2698
Montana	0.1307	0.1282	0.1267	0.0698	0.2068	0.1910	0.1153	0.2568
Nebraska	0.3162	0.3215	0.2179	0.2941	0.2901	0.3083	0.3070	0.3189
Nevada	0.3123	0.3101	0.1568	0.1828	0.1397	0.3064	0.2938	0.2990
New Hampshire	0.1749	0.1766	0.1633	0.1539	0.1815	0.1671	0.2087	0.2525
New Jersey	0.1648	0.2124	0.2030	0.1598	0.1830	0.1759	0.1851	0.2119
New Mexico	0.1575	0.1457	0.1175	0.0697	0.0619	0.0421	0.0877	0.1343
New York	0.3137	0.3202	0.1800	0.2823	0.2711	0.2791	0.2938	0.3011
North Carolina	0.3144	0.2742	0.1579	0.2559	0.2246	0.2252	0.2751	0.2932
North Dakota	0.3124	0.3050	0.2327	0.2699	0.2908	0.3150	0.2977	0.3155
Ohio	0.2699	0.2971	0.2696	0.2818	0.3102	0.3179	0.3088	0.3073
Oklahoma	0.1999	0.2446	0.1273	0.1081	0.0791	0.1339	0.1851	0.2021
Oregon	0.1920	0.3075	0.1363	0.2059	0.2947	0.2808	0.2305	0.3106
Pennsylvania	0.3135	0.3194	0.2066	0.3125	0.3060	0.3085	0.3060	0.3134
Rhode Island	0.2479	0.3073	0.2544	0.3111	0.2526	0.2855	0.2965	0.2979
South Carolina	0.3132	0.2017	0.2044	0.2817	0.2023	0.2641	0.2214	0.2721
South Dakota	0.2951	0.3178	0.2463	0.3170	0.2924	0.3158	0.2305	0.3169
Tennessee	0.2603	0.2412	0.1391	0.1691	0.1848	0.2257	0.1987	0.2749
Texas	0.1919	0.1769	0.1328	0.1134	0.0984	0.1116	0.1298	0.2261
Utah	0.3035	0.2921	0.1376	0.2112	0.2549	0.2525	0.2693	0.2998
Vermont	0.2713	0.2744	0.2368	0.2919	0.3213	0.3094	0.3111	0.2979
Virginia	0.2665	0.2887	0.2680	0.2304	0.3095	0.2817	0.2485	0.2956
Washington	0.3184	0.3210	0.2662	0.2574	0.3152	0.3034	0.3097	0.3110
West Virginia	0.1273	0.0686	0.1128	0.0204	0.0397	0.0243	0.0702	0.1387
Wisconsin	0.2472	0.2726	0.2671	0.2878	0.3110	0.3084	0.2965	0.3148
Wyoming	0.2886	0.2932	0.2178	0.2975	0.2593	0.3103	0.3023	0.3159

	-0.2	-0.15	-0.1	-0.05	0.05	0.1	0.15	0.2
Alabama	0.0472	0.0490	0.0645	0.0699	0.0654	0.0664	0.0676	0.0832
Alaska	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Arizona	0.0254	0.0480	0.0303	0.0241	0.0588	0.0707	0.0425	0.0607
Arkansas	0.0383	0.0365	0.0401	0.0461	0.0362	0.0336	0.0872	0.0675
California	0.0106	0.0113	0.0116	0.0106	0.0109	0.0145	0.0000	0.0121
Colorado	0.0632	0.0553	0.0471	0.0570	0.0540	0.0585	0.0425	0.0594
Connecticut	0.0521	0.0637	0.0664	0.0717	0.0700	0.0885	0.0473	0.0927
Delaware	0.0507	0.0480	0.0560	0.0521	0.0573	0.0712	0.0616	0.0683
District of Columbia	0.1060	0.1147	0.1128	0.1133	0.1391	0.1318	0.1382	0.1245
Florida	0.0099	0.0097	0.0110	0.0115	0.0118	0.0110	0.0000	0.0123
Georgia	0.0629	0.0713	0.0599	0.0595	0.0708	0.0719	0.0574	0.0746
Hawaii	0.0693	0.0623	0.0626	0.0635	0.0638	0.0638	0.0652	0.0692
Idaho	0.0031	0.0000	0.0000	0.0000	0.0037	0.0222	0.0000	0.0344
Illinois	0.0492	0.0510	0.0590	0.0589	0.0670	0.0574	0.0405	0.0672
Indiana	0.0557	0.0571	0.0549	0.0703	0.0466	0.0742	0.0466	0.0667
Iowa	0.0744	0.0950	0.1037	0.0958	0.1048	0.1061	0.0752	0.1091
Kansas	0.0886	0.1049	0.1088	0.1110	0.1070	0.1091	0.0962	0.1078
Kentucky	0.0550	0.0546	0.0582	0.0512	0.0955	0.1206	0.1214	0.1138
Louisiana	0.0367	0.0320	0.0238	0.0215	0.0287	0.0300	0.0334	0.0472
Maine	0.0173	0.0879	0.0077	0.0069	0.0044	0.0013	0.0013	0.0203
Maryland	0.0858	0.0915	0.0989	0.0947	0.0861	0.0810	0.0713	0.0794
Massachusetts	0.0618	0.0585	0.0696	0.0855	0.0879	0.0885	0.0578	0.0936
Michigan	0.0567	0.0566	0.0563	0.0660	0.0468	0.0511	0.0412	0.0667
Minnesota	0.0916	0.0862	0.0946	0.1182	0.1467	0.1298	0.1202	0.1434
Mississippi	0.0315	0.0378	0.0387	0.0389	0.0379	0.0457	0.0273	0.0446
Missouri	0.0428	0.0409	0.0368	0.0337	0.0301	0.0335	0.0332	0.0355
Montana	0.0390	0.0329	0.0329	0.0263	0.0421	0.0423	0.0203	0.0430
Nebraska	0.0346	0.0340	0.0368	0.0360	0.0367	0.0553	0.0531	0.0549
Nevada	0.0091	0.0119	0.0141	0.0106	0.0176	0.0147	0.0000	0.0165
New Hampshire	0.0269	0.0349	0.0256	0.0335	0.0236	0.0354	0.0000	0.0208
New Jersey	0.0175	0.0233	0.0238	0.0175	0.0175	0.0175	0.0312	0.0396
New Mexico	0.0164	0.0151	0.0088	0.0089	0.0109	0.0111	0.0290	0.0322
New York	0.1078	0.1179	0.1255	0.1246	0.1205	0.1156	0.1018	0.1286
North Carolina	0.0746	0.0699	0.0733	0.0650	0.0579	0.0665	0.0590	0.0727
North Dakota	0.0293	0.0318	0.0322	0.0275	0.0351	0.0378	0.0171	0.0386
Ohio	0.0359	0.0360	0.0355	0.0332	0.0334	0.0328	0.0315	0.0294
Oklahoma	0.0522	0.0671	0.0646	0.0646	0.0600	0.0659	0.0658	0.0546
Oregon	0.1184	0.1160	0.1139	0.1135	0.1183	0.1139	0.1005	0.1204
Pennsylvania	0.0135	0.0178	0.0153	0.0179	0.0210	0.0228	0.0000	0.0241
Rhode Island	0.0586	0.0477	0.0591	0.0469	0.0621	0.0613	0.0565	0.0608
South Carolina	0.0445	0.0000	0.0098	0.0022	0.0000	0.0001	0.0000	0.0000
South Dakota	0.0282	0.0358	0.0280	0.0379	0.0219	0.0258	0.0000	0.0274
Tennessee	0.0000	0.0000	0.0107	0.0147	0.0161	0.0208	0.0000	0.0163
Texas	0.0190	0.0215	0.0219	0.0213	0.0229	0.0218	0.0000	0.0222
Utah	0.0718	0.0689	0.0462	0.0482	0.0577	0.0494	0.0418	0.0642
Vermont	0.0874	0.0868	0.0991	0.0944	0.1019	0.0983	0.1019	0.0928
Virginia	0.0586	0.0596	0.0701	0.0560	0.0717	0.1008	0.0792	0.1044
Washington	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
West Virginia	0.0300	0.0300	0.0303	0.0300	0.0313	0.0313	0.0219	0.0296
Wisconsin	0.1231	0.1350	0.1435	0.1439	0.1517	0.1537	0.1536	0.1587
Wyoming	0.0151	0.0095	0.0165	0.0179	0.0155	0.0240	0.0000	0.0142