State Tax and Transfer Progressivity and the Household Consumption Response to Fiscal Stimulus*

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Abstract

This paper studies regional variation in the household Marginal Propensity to Consume (MPC) out of economic stimulus payments. For the 2001 stimulus episode, I find that the average household MPC in some U.S. states was up to 53 cents per stimulus Dollar. In other states, it was not statistically different from zero. Given recent empirical findings on preference heterogeneity as a determinant of MPCs, I estimate a measure of risk aversion for both state groups and find that households in high MPC states are less risk averse. Using a calibrated two-region consumption-savings model, I show that this kind of preference heterogeneity explains cross-state MPC differences. I empirically verify the model's predictions on financial precautionary behavior and I derive another testable implication of regional risk aversion differences; more risk averse state populations prefer fiscal policies which offer more social insurance. A new measure of state progressivity confirms that states in which I estimate higher risk aversion have more progressive taxes and transfers.

Keywords: Tax and Transfer Progressivity, Fiscal Policy, State and Local Taxes, Saving and Consumption, Income and Wealth Distribution

JEL Classification: D31, E21, E62, H2, H7

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1 Introduction

The heterogeneous-agent incomplete-markets framework has become the standard representation of the household sector in macroeconomic models. As a corollary, the Marginal Propensity to Consume (MPC) is currently a key object of interest. The MPC is the share of a transitory, unexpected income shock which a household consumes within a given time horizon, usually a quarter. Its distribution across households regulates the incidence and transmission of macroeconomic shocks and controls the effects of fiscal and monetary policy interventions.

Yet, measuring the size of the household MPC and identifying its determinants remains a challenge. For a transitory income shock of about \$500, widely different estimates have been reported, ranging from 0 to 50% for expenditures on non-durables in the quarter in which the shock was received.[1] Moreover, these average estimates mask considerable heterogeneity across households which cannot be explained by characteristics such as age, family size, income and wealth. For that reason, the latest research papers on MPC heterogeneity highlight the importance of unobservable characteristics, namely preference heterogeneity.[2]

This paper contributes a geographic dimension to the literature on household MPCs and studies the importance of risk aversion heterogeneity. Specifically, I investigate cross-state variation in the household consumption response to the fiscal stimulus payments ('tax rebates') of 2001. I find sizable cross-state MPC differences and, complementing recent empirical papers on the role of preference heterogeneity, I provide evidence that regional differences in household risk aversion are a driver of this variation. I also document that states in which I estimate lower average risk aversion have lower precautionary savings and less progressive tax and transfer systems. Both of these empirical findings support the argument that differences in risk aversion explain regional MPC differences.

The focus of my investigation is on the MPC out of stimulus payments as this program has become a persistent and sizable component of stimulus packages; direct payments to households have been distributed in all three of the last recessions, have been endorsed by four consecutive Presidents (Democrat and Republican) and constituted up to 20% of total spending in the most recent Covid stimulus packages. In general, recipients with children and low incomes receive

[1] See table 1 of Carroll, Slacalek, Tokuoka, and White (2017) for a survey. The MPC literature investigates changes in consumption behavior following income shocks due to stimulus payments or lottery wins or examines answers to hypothetical survey questions. Some papers also pursue non-experimental approaches and identify transitory income changes using semi-structural methods.

[2] For example, Parker (2017) finds that distinct intensities of impatience rationalize MPC heterogeneity. Laibson, Maxted, and Moll (2021) do so for present biased beliefs and Aguiar, Bils, and Boar (2020) for the intertemporal elasticity of substitution. Finally, Lewis, Melcangi, and Pilossoph (2021) underscore the importance of preference heterogeneity as a promising avenue for research on MPC heterogeneity.

more generous checks. However, geography is not a parameter of the stimulus check program. At the same time, research on preference formation provides evidence on the importance of local factors and emphasizes their regional diversity.[3] Accordingly, observationally identical households residing in different regions of the US receive the same amount of stimulus income but differ systematically in risk aversion. Thus, variation in household consumption changes after receiving transitory income provides a suitable environment to examine the role of this kind of preference heterogeneity as a determinant of household MPCs.

To explore if cross-state risk aversion heterogeneity can explain regional MPC discrepancies, I estimate a measure of risk aversion for households residing in those groups of states with the highest and lowest average household MPCs. To assess the quantitative effects of these measured differences in risk aversion, I build a two-region heterogeneous-agent model which features relevant determinants of consumption and savings choices as well as cross-state differences in risk aversion. The model shows that differences in risk aversion result in regional MPC differences which are similar to their empirical estimates.

Moreover, the model illustrates that risk aversion determines MPCs through two channels; first, less risk averse households hold fewer liquid assets for precautionary purposes. Thus, they are more likely to experience liquidity constraints and to exhibit hand-to-mouth consumption behavior (i.e. to have large MPCs out of stimulus income). I use measures of liquid wealth constructed from tax return data to confirm that households in high MPC states indeed hold fewer savings in liquid assets. Second, risk aversion determines the curvature of the household consumption function – it is steeper for less risk averse households. A numerical decomposition reveals that the former channel accounts for about 60% of the model's cross-state MPC differences while the latter accounts for about 30%.

Regional risk aversion heterogeneity has another unambiguous prediction on measurable state level outcomes; households who are less risk averse favor less progressive state tax and transfer policies because the value of consumption insurance provided by progressivity increases in risk aversion.[4] I derive this prediction from a political economy model and use it to support my argument that differences in risk aversion manifest themselves in measurable outcomes. I demonstrate that states in which I estimate higher household risk aversion have more progressive fiscal policies. I do so using a novel measure for the progressivity of state tax and transfer

[3]For example, Cesarini, Dawes, Johannesson, Lichtenstein, and Wallace (2009) and Dohmen, Falk, Huffman, and Sunde (2012) find that a large share of variation in preferences for risk can be explained by genetic heritage and local social environments. Both differ geographically in the US due to regional clusters of distinct immigrant groups.

[4]Throughout this paper, I aggregate the tax and transfer policies of local governments within each state and consider them as contributing to the mean progressivity of each state's tax and transfer system.

policies which captures that some states have high income tax rates for top earners and generous income support programs for the poor while others collect revenues using regressive sales and property taxes.

Economic theory predicts an ambiguous relationship between tax and transfer progressivity and MPCs. To compare and disentangle the effect of cross-state differences in risk aversion and progressivity on MPCs, I extend the consumption-savings model to capture this additional dimension of heterogeneity. I find that tax progressivity differences are insufficient to rationalize my empirical estimates of cross-state MPC variation. Instead, it is the difference in risk aversion which reconciles the model predictions with the empirical evidence. Finally, my paper also explores differences between states with respect to other characteristics determining household MPCs (labor market risks, minimum wage and credit market regulations). However, none of them differs systematically between states with high and low average MPCs so they are not suitable candidates to explain regional MPC differences.

The structure of this paper is as follows. Section 2 benchmarks my paper against related studies and flags its contributions. In section 3, I estimate MPCs of households for the 2001 tax rebate program and document sizable differences across US states. Section 4 estimates a measure of risk aversion for households residing in states where I find high and low MPCs. For these measured differences, section 5 computes average MPCs in a two-region consumption-savings model. This section also compares the model's predicted regional differences in financial precautionary behavior to empirical measures. In section 6, I provide additional evidence for differences in risk aversion across states by deriving and testing an implication on the relationship between risk aversion and the choice of state level fiscal policies. In section 7, I study the effect of state fiscal policies on household MPCs and investigate additional state characteristics which could be associated with cross-state differences in MPCs. Section 8 concludes.

2 Related Literature

My paper connects two different literatures. The first are the empirical and theoretical papers investigating the household consumption response to stimulus checks. The consumption response to the 2001 stimulus episodes is studied by, for example, Shapiro and Slemrod (2003a), Shapiro and Slemrod (2003b), Agarwal, Liu, and Souleles (2007) and Johnson, Parker, and Souleles (2006). For the same stimulus check episode Misra and Surico (2014) conduct an estimation in which they allow MPCs to vary across household groups with different demographic and economic characteristics. Contrary to this paper, my focus is on comparing MPCs of households residing in different groups of US states as they differ with respect to unobservable characteristics and reside in jurisdictions with systematic variation in taxes and transfers.

I focus on regional risk aversion differences as drivers of differences in regional MPCs because a growing number of empirical findings emphasize the importance of preference heterogeneity to explain household MPC heterogeneity. For example, Parker (2017) and Gelman (2021) document that households who are less patient have higher MPCs out of transitory income shocks. Moreover, several structural papers, for instance, Jappelli and Pistaferri (2014), Carroll, Slacalek, Tokuoka, and White (2017), Aguiar, Bils, and Boar (2020) and Laibson, Maxted, and Moll (2021) show that introducing preference heterogeneity into heterogeneous agent models allows to rationalize empirical MPC distributions.

The model environment in which I investigate the effects of differences in risk aversion and tax and transfer progressivity on MPCs is based on the single asset model of Kaplan and Violante (2021). This heterogeneous agent framework features all elements required to generate meaningful distributions of MPCs, i.e. uninsurable earnings risk and liquidity constraints, and allows for a tractable inclusion of different degrees of tax and transfer progressivity. Yet, my model differs from their earlier framework, presented in Kaplan and Violante (2014), as it is a one-asset model in which households choose the amount of *liquid* assets to accumulate for precautionary purposes.[5] I work with this structural environment because of a limitation in the availability of regional portfolio data; estimating the two asset model of Kaplan and Violante (2014) requires detailed measures of household portfolio compositions, in particular the share of liquid and illiquid assets.

The premier data source for this information is the Survey of Consumer Finances (SCF). However, the public use files of the SCF do not include information on respondents' state of residence. Moreover, the SCF is not designed to be representative at the state level. Thus, I cannot ascertain precisely to what extent cross-state differences in the portfolio compositions of households drive different MPCs, i.e. I cannot validate this particular mechanism of household MPC heterogeneity. Instead, I construct measures of liquid assets from tax return data provided by the Internal Revenue Service (IRS) to assess the predictions of my model with respect to the stocks of liquid assets across states.[6]

[5] The framework of Kaplan and Violante (2014) produces sizable consumption changes out of transitory income shocks as it features households who can be considered "wealthy hand to mouth". These households have large MPCs despite owning sizeable amounts of wealth as they hold substantial illiquid (housing) wealth, but little liquid assets. For that reason, their spending behavior is as if they were close to or at a liquidity constraint.

[6] Section C of the appendix provides more details on this limitation of the SCF data and shows how I construct a proxy measure of liquid assets by state.

The second literature my study contributes to is the large and growing number of research papers investigating the determinants and effects of differences in US state tax and transfer policies. Many of these papers consider policy choices of US state governments as a source of exogenous variation which allows to estimate causal relationships between policies and outcomes at the micro and macro levels.[7] The advantage of this approach over cross-country comparisons is that it allows to identify policy effects within a common institutional setting which alleviates concerns regarding the confounding role of unobservable national characteristics.

I complement these papers as I estimate regional differences in the consumption response to a federal stimulus program. As an explanation for the regional differences, I propose a specific form of preference heterogeneity, namely regional risk aversion differences. I focus on risk aversion to explain differences in regional MPCs since research on the formation of preferences emphasizes the role of local factors. For example, papers such as Cesarini, Dawes, Johannesson, Lichtenstein, and Wallace (2009) and Dohmen, Falk, Huffman, and Sunde (2012) find that a substantial share of individual variation in preferences can be explained by genetic heritage and local social environments. Both differ geographically in the US due to regional clusters of distinct immigrant groups. Related to this aspect, Guiso, Sapienza, and Zingales (2006) and Giuliano and Tabellini (2020) show that state populations with large shares of Scandinavian heritage have higher preferences for public insurance. Finally, Shigeoka (2019) and Malmendier (2021) emphasize that regional economic events, such as local recessions, corporate bankruptcies and natural disasters (floods, draughts) have profound effects on the formation of risk preferences.

I verify that regional differences in risk aversion have the capacity to materialize in measurable outcomes by studying progressivity differences of state fiscal policies; using a political economy choice model which is based on the environment presented in Heathcote, Storesletten, and Violante (2008), I show that risk aversion has sharp predictions on the desired degree of state fiscal progressivity – more risk averse voters prefer higher progressivity. I then characterize state tax and transfer progressivity using the measure presented by Fleck, Heathcote, Storesletten, and Violante (2021), which accounts for direct and indirect state taxes (income, sales, excise and property taxes) as well as the bulk of state transfer programs. As this measure captures potential progressivity trade-offs between different taxes and transfers, it provides a robust

[7] For a recent example studying the effect of state taxes on growth, see Fajgelbaum, Morales, Suárez Serrato, and Zidar (2019) and Akcigit, Grigsby, Nicholas, and Stantcheva (2021). For the effect of social insurance programs on individual outcomes, see Goodman-Bacon (2021) and Miller, Johnson, and Wherry (2021) (Medicaid) and Hsu, Matsa, and Melzer (2018) (Unemployment Insurance).

characterization of state fiscal policy choices.[8] Thus, I use observable fiscal policy differences across US states to verify that state populations differ with respect to risk aversion.

3 Average Household MPCs in different States

In this section, I document regional variation in the household marginal propensity to consume out of stimulus checks. I do so by investigating the 2001 stimulus check episode. Throughout my empirical analysis, I exploit a specific feature of the stimulus payment program; the amounts households received were determined by their *federal* taxable income. Accordingly, households residing in different states who had the same taxable income and the same relevant demographic characteristics (marital status, number of dependents) with respect to the federal income tax code received identical amounts of stimulus income.

For the 2001 stimulus check episodes, Johnson, Parker, and Souleles (2006) worked with the Bureau of Labor Statistics to include a special module to the Consumer Expenditure Survey (CE) which asked respondents in which month they received stimulus checks and how much they received. As the CE consists of several monthly interviews, the answers provided by survey participants allow to identify the effect of the stimulus check on consumption expenditures in the same and subsequent quarters.

The 2001 stimulus checks arrived between July and September of that year and all eligible households received them in the form of mailed checks. They came as advance payment to a retroactive reduction of the tax rate of the lowest federal income tax bracket from 15% to 10%. For the median recipient household, the stimulus amount was about $500. Importantly, the date at which households received the payment was effectively random; due to administrative constraints, they were sent to households according to the second-to-last digits of their social security number. As these numbers are effectively randomly assigned, the order in which households received their cash checks was uncorrelated with household characteristics.

Accordingly, comparing expenditure changes of households who received the stimulus income in a given time period with those who did not allows to identify the causal effect of the stimulus checks on changes in consumer expenditures, i.e. the MPC out of stimulus income. Thus, the baseline specification of Johnson, Parker, and Souleles (2006) to estimate consumption re-

[8]Other papers studying differences in state tax and transfer policies focus on specific groups of households, for example participants in a select transfer program. This limitation also applies to Fleck and Simpson-Bell (2021) who study the income insurance capacity of a large number of state tax and transfer programs but focus on the working poor.

sponses to receiving cash check income is

$$C_{i,t+1} - C_{i,t} = \gamma' X_{i,t} + \beta R_{i,t+1} + u_{i,t+1} + v_t \tag{1}$$

where i denotes households and t quarters. C are consumption expenditures on different categories, namely food, strictly nondurables and nondurables.[9] X includes a number of demographic household controls; age and changes in family composition which capture endogenous preferences driving changes in consumption growth. R measures the amount of stimulus checks received so β measures its average causal effect on changes in consumption expenditures, i.e. the MPC of household i. Its coefficient estimate measures by how many cents expenditures on a specific consumption category increased relative to receiving \$1 in stimulus check income. v_t are month fixed effects to control for seasonal consumption expenditure variation while $u_{i,t+1}$ absorb household specific variability. In this estimation, standard errors are corrected for heteroskedasticity and for serial correlation at the household level.[10]

Estimating MPCs by State My interest is to estimate regional differences in the household consumption response. Hence, I adjust the specification of equation (1) as follows; first, I include state fixed effects v_s. These control for time invariant cross-state differences which might explain different consumption responses. Some of these might be attributable to state differences in average geographic distances between consumers and shops or restaurants which may affect the timing and amounts of spending changes relative to receiving the stimulus check. Hence, controlling for state fixed effects allow me to rule out confounding influences of state characteristics which are correlated with state progressivity and slowly moving.

Second, I interact the stimulus check measure R with an indicator variable on the state of residence of household i, $d_{i,s}$. Thus, my augmented version of the baseline estimation equation (1) is as follows:

$$C_{i,t+1} - C_{i,t} = \gamma' X_{i,t} + \beta R_{i,t+1} \mathbf{d_{i,s}} + u_{i,t+1} + v_t + \mathbf{v_s} \tag{2}$$

where $\mathbf{d_{i,s}}$ is an indicator which I use to sort households into different states according to their state of residence reported in the CE. $\mathbf{v_s}$ represents state fixed effects.

[9]Food includes food consumed away from home and at home as well as purchases of alcoholic beverages. Nondurables is a broad measure of non-durable goods and services spending while strictly nondurables exclude semidurables like apparel. See Johnson, Parker, and Souleles (2006), appendix B for a detailed description of each category.

[10]Note that Johnson, Parker, and Souleles (2006) perform various tests for potential endogeneity in the timing of the rebate receipt, despite the randomized arrival time. They do not find substantial evidence for endogeneity. For that reason, my analysis follows their baseline specification shown in equation (1).

Data I use the dataset of Johnson, Parker, and Souleles (2006).[11] However, as their dataset does not include information on household state of residence, I merge each household with its record in the CE Public Use Microdata. Appendix A.1 provides more details on this procedure. The microdata contain the state of residence for about 86% of households. For the remaining households, they are suppressed to protect the anonymity of respondents.

Figure 1 shows the distribution of households by state. As this figure illustrates, households are unevenly distributed across states, with many having less than 100 interviewed households.[12] For that reason, I do not report results from estimating equation (2) at the level of individual states. Instead, I use the state-level average MPC estimates to sort households into different groups of states to guarantee a sufficient sample size. When doing so, I need to take into account that, due to the large number of households in a few states, different assignments can lead to differences in the balancedness of the groups. I explain my assignment strategy which addresses this concern in the following section.

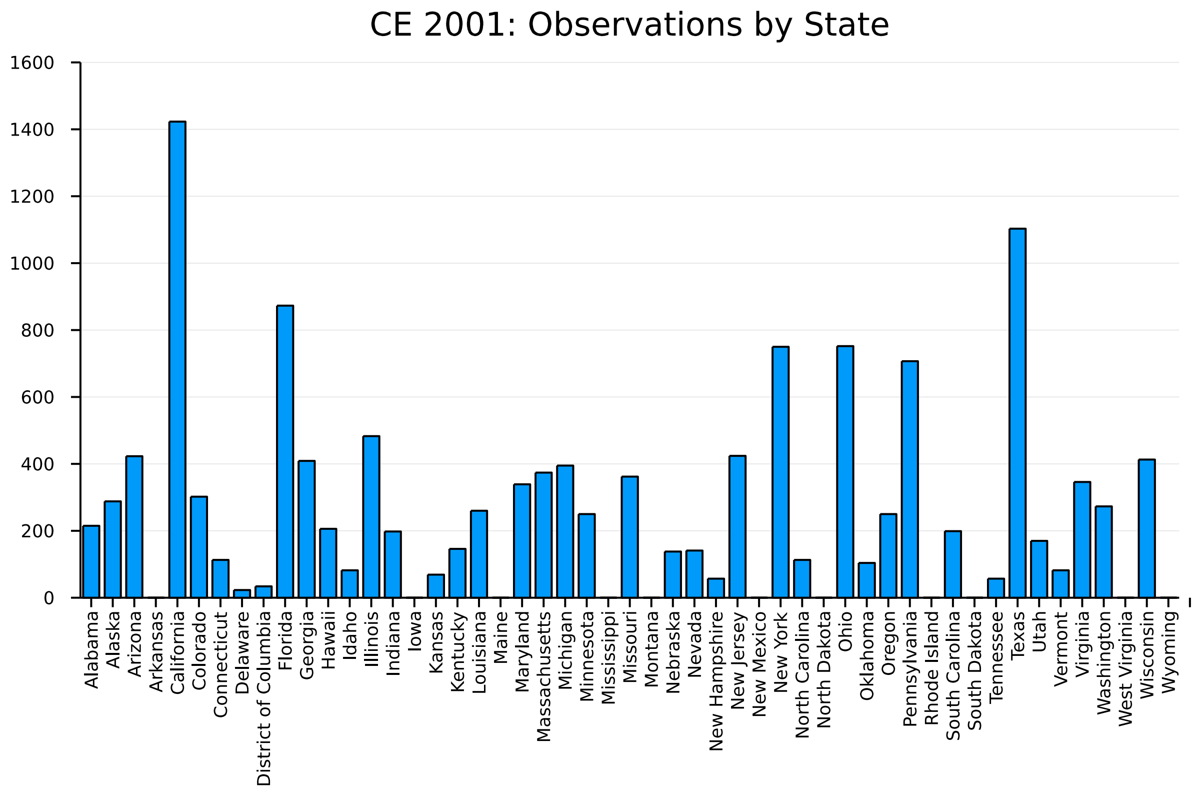

Figure 1: *Distribution of CE observations by state in the dataset of Johnson, Parker, and Souleles (2006).*

To assess how dropping observations without identified state of residence affects the sample

[11] Available here https://www.aeaweb.org/articles?id=10.1257/aer.96.5.1589.

[12] Note that this figure displays observations as the number of months a given household was interviewed in the CE. The median number of interviews in the CE is three, so the number of interviewed households is about three times smaller.

estimates, I repeat the baseline estimation of Johnson, Parker, and Souleles (2006), as specified in equation (1). The results presented in table 12 in appendix A.1 show that dropping households without identified state of residence does not alter the literature baseline results; the MPC estimates are identical, for food and nondurable goods up to the third digit. However, due to the loss of the observations without state identifier, the standard errors are slightly larger than reported by Johnson, Parker, and Souleles (2006).

3.1 MPC Estimates by State Groups

To quantify the effect of state tax and transfer progressivity, I estimate equation (2) using different specifications of $d_{i,s}$. As discussed above, the number of observations in my CE sample are not equally distributed across states. I take several steps to limit the effect of this shortcoming in my data on state average MPC estimates. First, to address the possibility that arbitrary concentrations of outliers might drive cross-state MPC discrepancies, I remove the top 0.1% of reported consumption changes. Second, I estimate equation (2) for several different subsamples of households. Specifically, I first rank all states according to their average MPC estimate. Next, I assign them into two groups using different ranking cutoffs and estimate MPCs for all households in each group.

I illustrate this strategy in more detail; my CE sample for 2001 allows me to identify households residing in 40 of the 51 US states. In the remaining states, the residence information is suppressed for all CE respondents. I begin by splitting these 40 states into two groups, one containing the ten states with the highest average household MPCs and the other containing all other (30) states. Given this split – which results in a different number of observations in each group – I estimate average household MPCs for each group as specified in equation (2).

Next, I change the group composition and assign the next ten states with high MPCs into the high MPC state group, leaving me with a total of 15 states in the high MPC and 25 in the low MPC group. Again, I estimate average MPCs in each group. I proceed in this fashion by subsequently lowering the cutoff for states to be considered high MPC. Accordingly, in my final estimation, I compare the 30 states with the highest average MPCs to the remaining ten states with the lowest average MPCs.

This estimation strategy achieves two objectives. First, I want to be able to identify non-linear relationships between state characteristics and household MPCs. Conducting different estimations for state groups with varying average MPC compositions allows to characterize this kind of relationship. Second, as households are unequally distributed across states, this strategy provides me with robust estimates which are not driven by an arbitrary cutoff in the assignment of households into two groups. In other words, this estimation approach strikes a reasonable balance between aiming to achieve a balanced sample in terms of number of observations and measured MPC differences.

Results The left panel of figure 2 presents the estimation results. From top to bottom, it shows average MPC estimates of different consumption categories for households in different groups of states. All estimates refer to consumption changes in the same quarter in which the stimulus check was received. Each figure displays MPCs referring to the different consumption expenditure categories defined by Johnson, Parker, and Souleles (2006); the top figure shows MPCs on food expenditures, the middle on strictly non durables and the bottom on non durables. By construction, each category nests the preceding one.

The number of states grouped into the high MPC category is shown on the x axis. For example, the estimates on the left side of each panel show mean MPC estimates of households residing in the ten states with the highest average MPCs (in blue) and the mean MPC estimate of households residing in all other states (in blue). Moving from left to right, the group composition changes in favor of tilting the comparison groups towards adding states with lower average MPC estimates into the high MPC state group. In the middle, at 20, the states are split into two equal groups. At the very right end, the estimates refer to mean MPCs in the ten states with the lowest average MPCs and the 30 states with higher average MPCs.

The numbers printed above each estimate in the top left figure refer to the number of CE observations in each of the groups. By construction, they do not change when estimating MPCs for different consumption categories. Howevr, as the number of states in each group changes, so does the number of observations in them. The most balanced sample results from splitting the households into 20 states (about 7,100 and 6,100 per group). As the split tilts towards states which are at the lower and upper ends of the average MPC scale, the absolute number of observation falls. This is an inevitable consequence of the unbalanced distribution of observations across states in the CE dataset (as illustrated in figure 1).

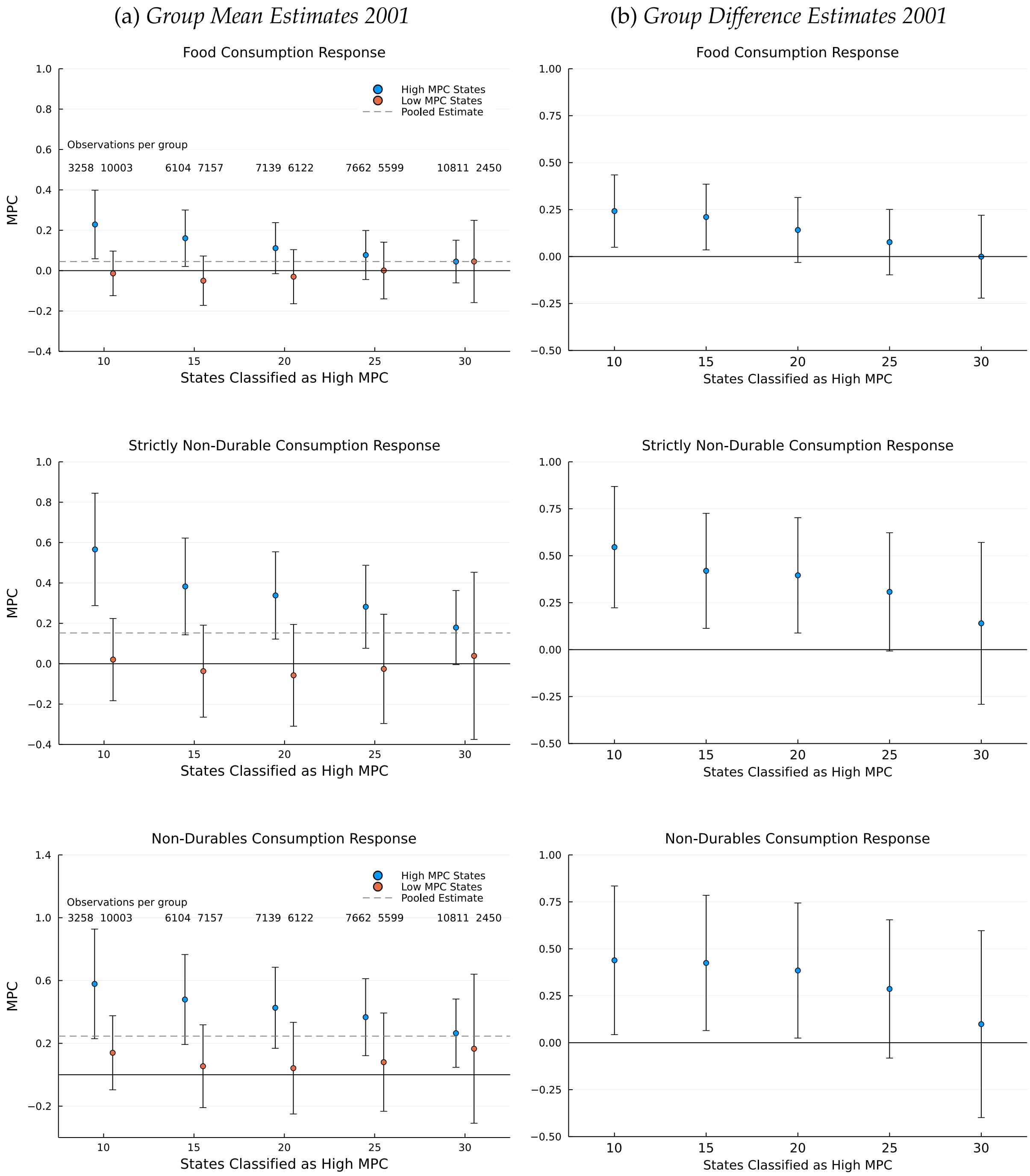

Figure 2: *Mean and group difference estimates of average MPCs in 2001 for different consumption categories. Error bars show 95% confidence intervals. Households sorted into different state groups according to state specific average household MPCs. Number of states identified in the CE sample: 40*

In the left panels of figure 2, the dashed line refers to the full sample estimate of the average MPC, i.e. *before* assigning households into state groups. For example, for food, it was estimated at 0.05, indicating an increase of 5 cents on food spending per Dollar received from stimulus checks in the same quarter in which the check was received. For expenditures on non-durables, this estimate is about 22 cents.[13] The vertical error bars show 95% confidence intervals.

In each panel, the point estimates of the mean MPC in the group of households residing in states with higher average MPCs is larger than the sample mean (with the exception of one food MPC estimate). However, it is always below the full sample mean and never different from zero for households residing in states with low average MPCs. Moreover, the gap in the mean MPC estimates grows as the group assignment compares households in states with higher average MPCs to those with lower average MPCs.

Furthermore, the mean MPC estimate of households in the states with the highest average MPCs is larger and statistically different from the full sample MPC estimate for food and strictly non durables; for food expenditures, the MPC estimate in the ten states with the highest average MPCs is 23 cents per Dollar received in stimulus check income but no different from zero in the 30 states with lower average MPCs. For strictly non durables, it is 56 cents (versus zero) and 58 cents (versus zero) for non durables, albeit this last estimate is marginally insignificant.

Finally, note that the mean MPC point estimate of households in states with the highest average MPCs is always different from zero (except for changes in food expenditures) while it is never different from zero for households in progressive states. This finding documents that the sample mean estimates reported by Johnson, Parker, and Souleles (2006) are driven by a small number of households with consumption behavior which is highly responsive to receiving cash checks. In other words, a small group of households in a few states drives the average non-zero consumption response.

In summary, these findings point to a large and systematic difference in the MPC out of stimulus payments across US states; the differences are especially large between households in those ten states where I found large average MPCs at the state level and those ten states where I found low average MPCs. Figure 3 shows that the ten states with the highest MPCs are states in the American South and Southwest. In those states, the average household MPC out of stimulus payments is estimated at 53 cents per Dollar of stimulus payment received. In the ten states with the lowest MPCs, which are in the West and Northeast, the point estimate is 18 cents but it is not statistically different from zero. Finally, for the remaining twenty states, the estimate is 24 cents per Dollar of stimulus payment received.

[13] Note that the estimates for strictly non-durables and non-durables are smaller than reported for the baseline estimation in appendix A.1. The reason is that removing the top 0.1% observations has a strong effect on these estimates. Recall that I remove them to avoid group difference estimates due to outliers.

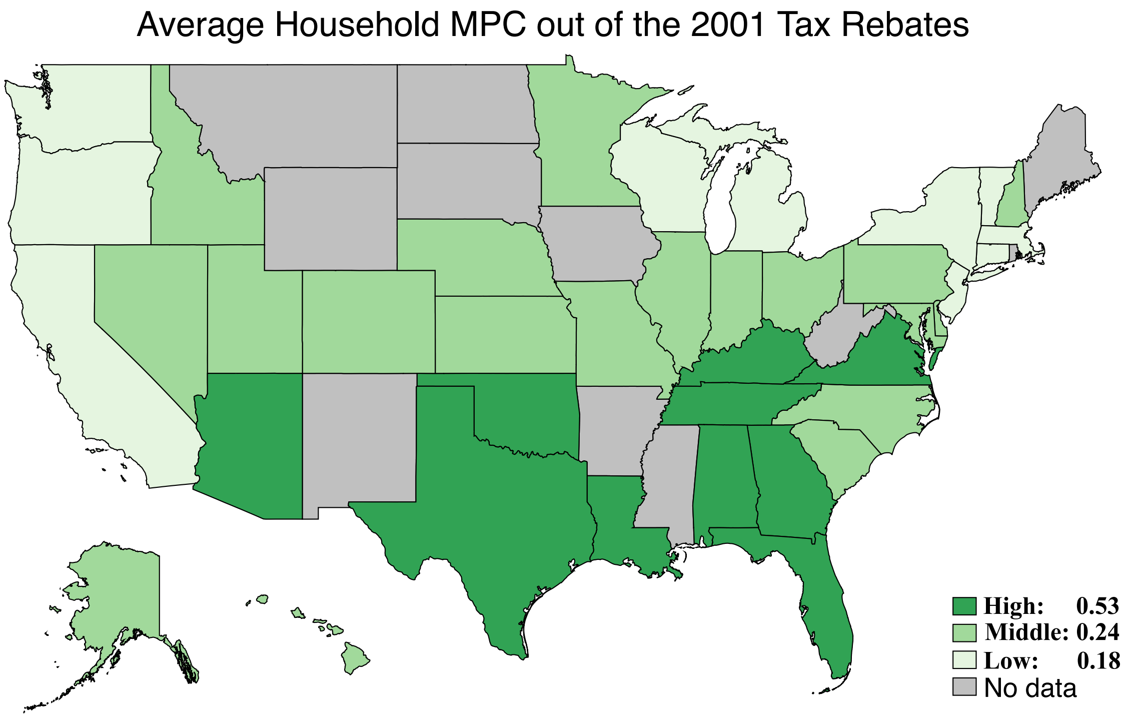

Figure 3: *The ten US states with the highest and lowest average household MPC in darkest and lightest green. Other states in medium green. The public CE datafile does not allow to identify households residing in gray colored states.*

Group Difference Estimates Except for the comparison between the highest and lowest MPC states, the group mean MPC estimates shown in figure 2 are generally not different from zero at the 95% level of statistical confidence. In addition, the 95% confidence intervals of different group estimates generally overlap. To assess whether there are significant group differences in the average MPCs out of stimulus check income, I modify equation (2) and estimate the following specification for each group assignment

$$C_{i,t+1} - C_{i,t} = \gamma' X_{i,t} + \beta R_{i,t+1} + \delta R_{i,t+1} d_{i,s} + u_{i,t+1} + v_t + v_s \tag{3}$$

In equation (3), δ captures the mean difference in the consumption response to receiving rebate amount R for households residing in different state groups. Thus, the size and standard error of its coefficient estimate provides a direct test whether the consumption response differs between state groups. The results of these tests are presented in the right panel of figure 2. For each consumption category and the same assignment of households into states as shown in the left (a) panels, the plots of panel (b) present the point estimates of $\hat{\delta}$ and their 95% confidence interval.

All coefficient estimates $\hat{\delta}$ are larger than zero (except one for the food expenditure category). Moreover, the 95% confidence intervals document that, for most group assignments, the mean MPC estimates of households in high MPC states are statistically different from, and larger, than those of households in states with lower average MPCs. Moreover, they corroborate the evidence shown in the left hand side panels; the MPC differences are most pronounced when considering the states with the highest and lowest MPCs.

Taking stock, these empirical findings demonstrate that the household consumption response to stimulus checks differs between groups of states. In a group of ten states in the American West and Northeast, the MPC out of stimulus income is never different from zero for no consumption category. In states in the South and Southwest, it is always larger than zero and profoundly larger than the full sample mean for food and strictly non durable consumption expenditures.[14]

3.2 Comparing States with the Highest and Lowest Average Household MPCs

The results presented in the preceding section point to large regional differences in the household consumption response to the stimulus check program of 2001. A candidate explanation for these differences are systematic differences in observable household characteristics across states. For example, differences in (changes of) family compositions, household head ages, incomes and liquid asset holdings may account for the estimate discrepancies, irrespective of any unobservable characteristics. In particular, a larger share of households in the high MPC states who can be considered liquidity constrained might account for the cross-state variation in estimated MPCs.

Note that the baseline MPC estimation presented in equations (2) and (3) controls for changes in family composition and the age of the household head. The latter characteristic is predictive of large MPCs as younger individuals have higher expected future earnings growth but limited access to credit markets. Two more household characteristics which are predictive of large MPCs are low income and low holdings of liquid assets. However, controlling for them in the baseline estimation is problematic for two reasons. First, household income is endogenous to the probability to receive a tax rebate as well as its magnitude. Second, Johnson, Parker, and Souleles (2006) document a non-linear relationship between MPCs and levels of income and liquid assets. Accordingly, a linear estimation specification is not suitable to capture the effect of those two variables on household MPCs.

[14] Figure 8 in appendix A.3 presents analogous estimation results for 2008 and provides a detailed comparison to the results of 2001.

	10 Highest MPC States AL, AZ, TN, FL, KY, LA, GA, OK, TX, VA	10 Lowest MPC States MA, CA, MI, CT, WA, NJ, NY, OR, VT, WI
Share of all observations (N=5,708)	%	%
Age < 39	28.4	28.3
Income < \$35,000	33.2	34.1
Income < \$15,000	13.4	12.6
Liquid Assets < \$5,000	*31.8*	*24.2*
Liquid Assets < \$1,000	*18.7*	*13.3*

Table 1: *Comparing shares of liquidity constrained households in the ten highest and lowest MPC states. Liquid assets (checking, savings accounts) missing for 50% of observations, income for 25%.*

To investigate if cross-state differences in household income and liquid assets might explain my findings on cross-state MPC differences, I conduct a more detailed investigation in which I focus on comparing the ten states with the highest and lowest average household MPCs. Specifically, I keep only observations residing in any of the states ranked as bottom and top ten according to state level MPC estimates. Table 1 summarizes the variables predictive of high MPCs in both samples.

As this table illustrates, the share of households in both groups of states which can be considered liquidity constrained from an age and income perspective is very similar; about 28% of household heads are below the age of 39 and about 33% (13%) can be considered to have low (very low) incomes.[15] Thus, cross-state differences in these dimensions are unlikely to explain regional MPC variation. Regarding the distribution of liquid assets, the table indicates that the share of households with low levels of liquid assets is larger in the ten states with the highest MPCs. However, a caveat to this discrepancy is that this variable is missing for a large number of households in the CE; in both state groups, it is available only for about 50% of all observations.

To investigate if liquidity constrained households residing in the different state groups differ in their consumption response to receiving cash checks, I again estimate equation (3) where I now set $d_{i,s} = 0$ for households residing in low MPC states (making them the base group) and $d_{i,s} = 1$ otherwise. Moreover, I estimate the equation separately for observations who have low incomes (below \$35,000) and high incomes (above \$35,000).

Columns (1) to (3) of table 2 show the baseline estimation results for households in both state groups before splitting them into different income groups. Compared to households in the

[15]These values are similar the ones used by Johnson, Parker, and Souleles (2006) to split the sample into different age and income groups. Note that the income measure provided in the CE refers to family income *before* all taxes.

	All Incomes			Low Incomes			High Incomes		
	Food	S. nondurable	Nondurable	Food	S. nondurable	Nondurable	Food	S. nondurable	Nondurable
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\hat{\delta}$: Group Difference	0.233*	0.596**	0.538*	0.046	0.460*	0.571**	0.414**	0.806**	0.748*
	(0.125)	(0.235)	(0.278)	(0.195)	(0.241)	(0.288)	(0.180)	(0.354)	(0.408)
Age	0.618	0.707	1.473*	-0.280	-0.330	0.106	0.848	1.509	1.253
	(0.378)	(0.669)	(0.888)	(0.376)	(0.573)	(0.771)	(0.938)	(1.649)	(2.183)
Change adults	85.454*	213.022**	298.693**	58.998	64.054	42.920	70.110	109.137	235.538
	(48.287)	(106.098)	(117.252)	(47.203)	(62.049)	(79.621)	(66.126)	(182.750)	(202.772)
Change children	38.158	78.634	151.417	24.520	70.753	139.964	-38.389	-145.681	-119.960
	(67.942)	(112.002)	(125.326)	(51.382)	(80.468)	(98.628)	(76.917)	(179.190)	(204.632)
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
N	6,475	6,475	6,475	2,286	2,286	2,286	2,432	2,432	2,432
R^2	0.009	0.014	0.014	0.015	0.019	0.015	0.021	0.027	0.032

Table 2: *Comparing household MPCs in the ten ten states with the highest and lowesst average household MPCs. Income is missing in the CE sample for 1,607 observations. To make sure that outliers do not drive estimated group differences when comparing the low and high income subgroups, I trim the bottom and top 1% of dependent variable observations.*

low MPC states, households in high MPC states have larger estimated average MPCs for each consumption category. The estimates of δ indicate that the mean consumption response in these states is about 23 cents larger for food, 60 cents larger for strictly nondurables and 54 cents larger for nondurables per Dollar received in stimulus income. All of these differences are significant at the 90% or 95% level of statistical confidence.

Columns (4) to (6) of table 2 show the estimation results when I compare households with low incomes in both state groups. Despite a substantial drop in the number of observations (income is missing for about 1,600 observations), I find that MPC differences between households in high and low MPC states remain sizable even when focusing only on households with (equally) low incomes.[16] While there is no statistical difference in the food MPC, low income households in high MPC states have larger MPCs for strictly nondurables and nondurables. A similar pattern applies to households with high incomes, as reported in columns (7) to (9); MPC estimates in the high MPC states are larger and significantly different for all consumption categories. These findings provide evidence against the concern that MPC differences between the state groups are due to differences in (mean) household incomes. Instead, even conditional on having low income, households in the high MPC states have systematically larger MPCs than households in the low MPC states.[17]

[16]The number of observations printed in the table indicates how often each household was interviewed. The median number of interviews in my CE sample is 3.

[17]When I repeat the estimation for households with low levels of liquid assets (below $5,000), I find similar results; for consumption expenditures on nondurables, households with low levels of liquid assets spend about 35 cents per Dollar more in high MPC states than in low MPC states. This differences is significant at the 90% level of statistical confidence.

Finally, I also consider that differences in estimated household MPCs between low and high MPC states might be driven by regionally distinct intensities of the 2001 recession. If this recession was associated with larger losses of jobs and earned incomes in some states, a larger fraction of households could be facing liquidity constraints. Moreover, I also investigate if states differed systematically in their policy response to the recession. For example, some state governments might have provided discretionary tax relief to homeowners and state employees or provide other forms of income support.[18] However, as discussed in appendix A.2, none of these channels help to explain more of the cross-state variation in MPCs.

4 Cross-State Differences in Risk Aversion

Recent empirical studies document the importance of household preferences as a determinant of MPCs. For example, Parker (2017) and Gelman (2021) demonstrate that heterogeneity in impatience explains a substantial share of MPC variation after controlling for household observables. Given this evidence, I now inspect if differences in MPCs across states correlate with systematic differences in household preferences. I focus on differences in risk aversion since a large literature documents that regional factors play a key role for the formation of risk preferences. For instance, most recently, Shigeoka (2019) shows that exposure to local economic recessions results in higher risk aversion of individuals who experienced them as young adults.

Following Mankiw and Zeldes (1991), numerous papers estimate risk aversion using household level consumption data. The starting point of these papers is the Euler Equation derived from an isoelastic utility function such as the Constant Relative Risk Aversion (CRRA) function. This Euler Equation determines intertemporal consumption choices given preference parameters and measurable variables. It is given as

$$\mathbb{E}\left[\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma} R_{t+1}\,\beta\right] = \mathbb{E}[\varepsilon_{t+1}] = 1 \tag{4}$$

where γ is the coefficient of relative risk aversion which captures the individual's aversion to fluctuations in intertemporal consumption. C_{t+1} and C_t denote consumption expenditures in consecutive time periods while R_{t+1} is a measure for the expected rate of return on financial investments. β represents the rate of time preference.

It is common to re-write this equation using a log-linear (first-order) approximation. In this

[18] Due to the balanced budget requirements of state governments, such measures can only play a minor role in stabilizing disposable incomes.

form, it is given as

$$\Delta \log C_{i,t+1} = \alpha + \frac{1}{\gamma} \log(R_{t+1}) + e_{i,t+1} \tag{5}$$

where α contains β as well as higher moments of the consumption growth and interest rate distribution. $e_{i,t+1}$ contains errors related to the household's expectations on the future rate of return as well as errors in the measurement of consumption expenditures and in the approximation. The left hand side variable denotes changes in (log) consumption expenditures between consecutive periods.

I estimate this equation using a common specification and estimation strategy. Specifically, I employ an instrumental variable approach and generalized method of moments (GMM) estimator to obtain estimates of γ for households residing in the ten highest and lowest MPC states using this estimation equation

$$\Delta \log C_{i,t+1} = \delta_1 D_1 + ... + \delta_{12} D_{12} + \frac{1}{\gamma} \log(R_t) + \phi \Delta \log X_{i,t} + u_{i,t+1} \tag{6}$$

In this specification, t denotes quarters, i households and X a vector of household characteristics. D_j are month dummies which absorb time preference differences to ensure that the estimate of γ is not confounded by variation in this dimension of preference heterogeneity. Finally, R_t is a measure for the real rate of return on financial investments. To account for the endogenous relationship between this variable and the innovation term, I instrument it with a number of different variables.

Table 3 presents the results of estimating equation (6). In the first column, I instrument $\log(R_t)$ using lags of the (log) real Treasury bill rate of return. When I use all observations in my sample, I find a value of 2.21 for $\hat{\gamma}$. When I use only observations residing in the ten states with the highest average household MPCs, I find an estimate of 2.35. For households in the ten states with the lowest average MPCs, this estimate is 1.97. All of these point estimates are statistically significant at the 95% level of statistical significance. Moreover, when I perform a group difference (Wald) test for the point estimates of the high and low MPC states, I find a p-value of 0.044 which indicates that these two estimates are different from each other at the 95% level of statistical significance. As shown in column two, I obtain similar results when I use an extended set of instruments which also includes a measure of stock returns in addition to rates of return for fixed income savings instruments.

In the lower panel of table 3, I present estimates $\hat{\gamma}$ obtained from using households which hold positive amounts of liquid assets. This subsample includes only households which are not liq-

	Instrument Set 1 $\hat{\gamma}$	Instrument Set 2 $\hat{\gamma}$
All observations	2.21** (1.02)	2.30** (0.97)
10 lowest MPC states	**2.35**** (1.12)	**2.41*** (1.27)
10 highest MPC states	**1.97**** (1.00)	**1.94**** (0.82)
p-value Wald Test: $\gamma_H = \gamma_L$	*0.044*	*0.042*
Only asset holders	2.32* (1.26)	2.34* (1.22)
10 lowest MPC states	2.41* (1.24)	2.50* (1.40)
10 highest MPC states	1.88 (1.33)	1.94* (1.11)
p-value Wald Test: $\gamma_H = \gamma_L$	*0.083*	*0.091*

Table 3: ** 10%, ** 5% level of significance (standard errors). Instrument Set 1: lagged log real Treasury bill rate. Instrument Set 2: lagged log real Treasury bill rate, lagged log real NYSE return*

uidity constrained and so differences in the expected interest rate affects differences in their intertemporal consumption choices. As this variable is missing for about 50% of all observations, the standard errors increase substantially which results in an overall loss of statistical significance. Still, for both sets of instruments, I find that the estimated coefficient of relative risk aversion is larger in the ten states with the highest MPCs. Moreover, the difference between coefficient estimates between households in the two groups of states is significant at the 90% of statistical significance.[19]

In summary, the estimation results presented above indicate that households in high and low MPC states differ with respect to an unobservable characteristic, i.e. risk aversion. In fact, risk aversion is inversely related to MPCs; in those states where I found high household MPCs in section 3, my estimates of risk aversion are lower than in those states where I found low MPCs. Given this evidence, I now turn to quantifying the degree of cross-state MPC variation which can be explained by the measured differences in risk aversion in the next section.[20]

5 The Effect of Risk Aversion on MPCs

In this section, I conduct a numerical investigation to quantify the effect of measured differences in risk aversion on cross-state variation in household MPCs out of stimulus income. I conduct this investigation using a heterogeneous-agent incomplete-markets model with stochastic

[19] In appendix B.1, I also present results of tests for instrument relevance and exogeneity. These tests indicate strong and exogenous instruments.

[20] In appendix B.2, I present and implement a risk aversion estimation approach which is similar to the MPC estimation presented in section 3. In this estimation, I also include state level measures for earnings risk and other state level controls. The findings of this estimation point in the same direction; household risk aversion is larger in state groups where average household MPCs are large.

labor income and a single (liquid) asset. This class of models generates larger MPCs than representative agent frameworks for three reasons. First, in equilibrium, these models feature agents with little or no (liquid) wealth. As those agents are ready to consume most (all) of any additional liquidity available to them, they have large positive consumption responses to transitory changes in liquid wealth provided by stimulus checks.

Second, market incompleteness and liquidity constraints coupled with stochastic income create two more sources of high MPCs; agents aiming to smooth consumption insure themselves against low income realizations by accumulating assets for precautionary reasons.[21] This precautionary motive becomes weaker as the level of wealth increases. Thus, the consumption function of these models is concave in wealth so that households with low or medium levels of wealth can display sizable MPCs. Finally, preference heterogeneity of households can also lead to large MPCs out of transitory liquidity shocks.[22]

Thus, this model is a suitable environment for my objective as it allows to identify the mechanisms through which risk aversion affects MPCs. First, the model makes testable predictions on the distribution of liquid assets across states. These differences are the result of differences in financial precautionary behavior associated with differences in risk aversion. Hence, to verify the importance of this mechanism, I can take these predictions to the data and study whether cross-state differences in MPCs are associated with differences in portfolio liquidity. Second, the model allows to quantify differences in MPCs which are driven by differences in the curvature of the household consumption function due to distinct intensities of risk aversion. While it is generally not possible to verify these differences empirically, the model allows to compute the share of MPC variation due to this particular mechanism.

5.1 Model Environment

Households The economy is populated by a continuum of infinitely lived households i and time is discrete. Households have a rate of time preference β and derive utility from consumption based on CRRA preferences. They supply labor inelastically and earned income $y_{i,t}$ follows a transitory-persistent process with persistence parameter ρ. Transitory (persistent) innovations ϵ_t (η_t) are drawn from a normal distribution with mean zero and variance σ_ε^2 (σ_η^2). Households have access to a risk free, one period, liquid asset b_t which is available in infi-

[21] This effect is driven by utility functions implying prudence i.e. $u''' > 0$.

[22] Examples of ex-ante household heterogeneity studied by the literature are the ability to generate different returns to wealth, higher tolerance to consumption fluctuations, or differences in self-control or impatience.

nite net supply and pays an exogenous, constant return $\bar{r}$.[23] This rate of return is such that $\beta(1+\bar{r}) < 1$ so households desire to frontload consumption.

This environment defines the household optimization problem as follows:

$$\max_{c_t} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\gamma}}{1-\gamma} \tag{7}$$

s.t.

$$c_t + b_{t+1} = (1+\bar{r})b_t + y_t \tag{8}$$

$$b_{t+1} \geq \underline{b} \tag{9}$$

$$y_t = z_t + \varepsilon_t \tag{10}$$

$$z_t = \rho z_{t-1} + \eta_t \tag{11}$$

$$\varepsilon_t \sim N(0, \sigma_\varepsilon^2) \tag{12}$$

$$\eta_t \sim N(0, \sigma_\eta^2) \tag{13}$$

The solution to the household's problem is characterized by two policy functions; $c^*(a,y)$ for consumption and $b'^*(b,y)$ for liquid wealth next period. These policies induce the stationary distribution $\mu(b,y)$ over the state space where $\mu(b)$ is the marginal distribution of liquid wealth. The individual dynamics of consumption choices are determined by the model's first order condition with respect to c_t, which results in a standard Euler Equation.

$$\mathbb{E}_t \left(\beta(1+\bar{r}) \left(\frac{c_{t+1}}{c_t} \right)^{-\gamma} \right) \begin{cases} = 1 & \text{if } b_{t+1} > \underline{b} \\ \leq 1 & \text{else} \end{cases}$$

While the model does not permit closed form solutions for the marginal propensity to consume out of transitory income shocks (MPC), they can be computed numerically for each element of the state space using the optimal consumption policy c^* as

$$mpc(x; b, y) = \frac{c^*(b+x, y) - c^*(b,y)}{x} \tag{14}$$

where x represents a one-time unanticipated windfall of cash-on-hand, i.e. liquid wealth.

Parameterization and Calibration Strategy Without ex-ante heterogeneity in households, plausible calibrations of single asset models cannot replicate empirical MPC distributions –

[23] This liquid asset model is isomorphic to a two asset model a la Kaplan and Violante (2014) in which the illiquid asset has prohibitively large liquidation costs.

Parameter (Quarterly Freq.)	Value	Description	Target/Source
Externally Calibrated			
γ	2.21	Risk Aversion	Pooled Sample Estimate
ρ	0.988	Persistence	Kaplan, Violante (2021)
σ_η^2	0.0108	Persistent Innovation	Kaplan, Violante (2021)
σ_ε^2	0.2087	Transitory Innovation	Kaplan, Violante (2021)
$\underline{b}$	0	Borrowing Limit	
$\bar{r}$	0.0025	Interest rate	
Internally Calibrated			
β	0.961	Time Preference	22% MPC, Pooled Sample Estimate

Table 4: *Parameter values of the baseline calibration*

	Average MPC		Mean liquid wealth/mean income		Hand-to-mouth (htm, %)	
	Model	Estimate	Model	Data	Model	Data
National Economy	0.22[1]	0.22	0.53	0.52[2]	13.0	14.3[2]

Table 5: *Model Results of the Baseline 'National Economy' Calibration.* [1]*Targeted,* [2]*Source: Survey of Consumer Finances (SCF)*

they fall short of an order of magnitude in matching average MPCs. Thus, the common approach to reproduce realistic MPCs is to target distributions of liquid wealth using different values of the household discount factor β.[24] Accordingly, I calibrate the model at the quarterly frequency by selecting a fixed value for the interest rate and then choosing a value of β which provides the average MPC I estimated for households in all states (i.e. before splitting into state groups). I use the value for the average MPC out of non durables which is about 22% (see figure 2, lower left panel). For the coefficient of relative risk aversion, γ, I use the value which I estimated for the entire sample, i.e. 2.21. Table 4 shows all parameter values I use for the model calibration.

5.2 Results

Baseline Results Table 5 presents the model results of the baseline ('National Economy') calibration. At the value of β producing the target MPC, the mean (liquid) wealth to income ratio in the model is about 0.53. Thus, agents hold about half of their income in liquid assets. The share of hand-to-mouth households – which have particularly high MPCs – is 13%.[25] The corresponding empirical moments computed from the Survey of Consumer Finances (SCF) are

[24] For that reason, a partial equilibrium approach is particularly useful as it allows to move the discount factor independently of the interest rate to target a desired average MPC. In general equilibrium, income uncertainty leads to over accumulation of assets so that he discount rate and the interest rate are not independent.

[25] To classify households as hand-to-mouth, I use the definition of Kaplan and Violante (2021); hand-to-mouth households are those who hold less than 50% of their monthly income in liquid assets.

	Average MPC		Mean liquid wealth/mean income		Hand-to-mouth (htm, %)	
	Model	Estimate	Model	Data	Model	Data
Low Risk Aversion State	0.31	0.53	0.45	0.42[3]	17.3	12.1[3]
High Risk Aversion State	0.15	<0.18	0.60	0.47[3]	10.0	9.4[3]

Table 6: *Model Results of the Low and High Risk Aversion Calibration.* [3]*Constructed from IRS tax return data*

0.52 and 14.3. Thus, even though they are not targeted, the model provides a good fit for the empirical liquid wealth distribution.[26]

High and Low Risk Aversion States My interest is to evaluate if the cross-state differences in measured risk aversion can explain a substantial share of cross-state MPC differences. Accordingly, I now extend the model to the case of two small open economies (which I call 'states' henceforth). I do so by keeping all parameters at their baseline calibration values but allow for cross-state differences in γ; in the low risk aversion state, I set it equal to $\gamma_L = 1.97$. In the high risk aversion state, I set it equal to $\gamma_H = 2.35$. Note that this calibration strategy keeps the interest rate constant across states. Thus, in the model, any cross-state differences in MPCs and liquid asset distributions are exclusively driven by differences in risk aversion.

Table 6 presents the results for the low and high risk aversion calibration. For the low risk aversion state, the average MPC increases to 0.31. This value approaches the empirical MPC estimate in the low risk aversion states (0.53) and is remarkably larger than the corresponding value in the national economy calibration (0.22). In the high risk aversion state, the model average MPC is 0.15. The corresponding empirical point estimate is 0.18. However, this estimate is not statistically different from zero. Accordingly, the model value is in the range of plausible values of its empirical counterpart.

Regarding financial precautionary behavior, the model results show that, in equilibrium, more risk averse households accumulate larger stocks of precautionary savings; the ratio of mean liquid wealth over mean income is larger in the high than in the low risk aversion state (0.60 versus 0.45). Thus, agents in the high risk aversion state are less likely to face liquidity constraints. This effect is also visible in the model share of hand-to-mouth households. It is 17.3% in the low risk aversion states and only 10% in the high risk aversion state. As this group has

[26] I compute this measure of liquid wealth using information on bank accounts and directly held stocks and bonds net of credit card debt. The ratio of liquid wealth to output in the model is 0.28 which is similar to its empirical counterpart (0.26).

	Low Risk Aversion State	High Risk Aversion State
Δ MPC	0.09	-0.07
Asset Distribution	59	61
Consumption Function	27	28
Interaction	13	11

Table 7: *Average MPC Decomposition; relative to National Economy (in %)*

particularly large MPCs, the difference in this share is a key driver in the differences of the average MPC across the two states.

Taking the model predictions on differences in liquid assets to the data is a challenge. The reason is that the SCF does not publish a state identifier variable. More fundamentally, as the survey is not designed to be representative at the state level, it cannot be used to characterize differences in household liquid asset holdings in different states. Hence, to evaluate the model's predictions on regional differences in precautionary savings, I construct a measure of liquid assets relative to income using information from tax returns provided by the Statistics of Income (SOI) of the Internal Revenue Service (IRS). Details on the construction of these measures are provided in section C of the appendix.

The empirical moments of regional household portfolio differences are displayed in colums (4) and (6) of table 6. They provide support for the predictions of the model; in low risk aversion states, the empirical ratio of mean liquid wealth over mean income is 0.42 while it is 0.47 in states with high risk aversion. Thus, the estimated differences in regional risk aversion correspond to regional differences in financial precautionary behavior. These differences are also measurable in the share of hand-to-mouth agents in both groups of states; for the low risk aversion states, the share is 12.1% while it is 9.4% in the high risk aversion states.

These findings show that risk aversion affects MPCs through regional differences in financial precautionary behavior. However, risk aversion also determines the curvature of the consumption function. As the slope of the consumption function determines consumption responses to changes in income, this mechanism also contributes to differences in MPCs across high and low risk state groups. Hence, I conduct a numerical decomposition to disentangle and quantify the importance of differences in financial precautionary behavior and the shape of the consumption function.

Specifically, let $\mu^{NE}(b,y)$ denote the distribution of households in the state space of the model with the baseline ('National Economy') calibration. Let $mpc^{NE}(b,y)$ denote the state specific

MPC and $\overline{mpc}^{NE}$ the average MPC of this model. The difference to the average MPC in a model with the state specific calibration (high or low risk), $\overline{mpc}^{s}$ can then be decomposed into three distinct contributions as follows

$$\overline{mpc}^{s} = \overline{mpc}^{NE} \tag{15}$$
$$+ \int_{B\times Y} \left(mpc^{s}(b,y) - \overline{mpc}^{NE}\right) d\mu^{NE}(b,y) \tag{16}$$
$$+ \int_{B\times Y} mpc^{NE}(b,y) \left(d\mu^{s}(b,y) - d\mu^{NE}(b,y)\right) \tag{17}$$
$$+ \int_{B\times Y} \left(mpc^{s}(b,y) - \overline{mpc}^{NE}\right) \left(d\mu^{s}(b,y) - d\mu^{NE}(b,y)\right) \tag{18}$$

where equation (16) captures average MPC differences resulting from discrepancies in the curvature of the consumption function and equation (17) those due to differences in the stationary distributions of the two models, i.e. distinct concentrations of households in the (b, y) state space. Finally, equation (18) describes the interaction between both.

Table 7 presents the results of decomposing MPCs between the baseline ('National Economy') calibration and the high and low risk aversion states. It shows that about 60% of the MPC discrepancies are due to differences in asset distributions, i.e. financial precautionary behavior. About 30% are explained by differences in the shape of the consumption function. Thus, while the latter mechanism has a smaller effect than the first one, it still accounts for a sizable share of the differences in the average MPC. This finding emphasizes that controlling for household observables, i.e. differences in liquid wealth, is not sufficient to capture the effect of risk aversion on MPCs – it also materializes via (unobservable) differences in the shape of the consumption function.

In summary, the model illustrates that risk aversion affects MPCs through two mechanisms. First, less risk averse households are more likely to be liquidity constrained, i.e. to have high MPCs due to lower holdings of precautionary savings. This mechanism is supported by empirical evidence from both the CE (see table 2) as well as the measure of liquid asset over income ratios I constructed from tax return data. Second, differences in risk aversion affect the curvature of the consumption function. Hence, even conditional on holding identical amounts of liquid assets, less risk averse households have a larger MPC out of transitory income shocks.

To generate these findings, I calibrated the model using the regional estimates of risk aversion coefficients presented in section 4. These model inputs are the key drivers of the cross-state MPC differences in the model. Given their pivotal importance, I turn to provide additional evidence for regional differences in risk aversion in the next section.

6 Inferring Risk Aversion from State Tax and Transfer Progressivity

In this section, I provide evidence on differences in risk aversion across states using an auxiliary channel: I compare differences in measurable state level outcomes which reflect risk aversion preferences of state residents. Specifically, I focus on the progressivity of state tax and transfer systems. Using a political economy model to determine the choice of tax and transfer progressivity, I show that higher risk aversion has clear implications for the degree of public progressivity desired by state residents; the value of insuring consumption risk i.e. the value attached to completing markets, is monotonically increasing in risk aversion. Accordingly, households with higher risk aversion tolerate the distortions to labor supply introduced by progressive taxes in return for stable disposable incomes.

I derive this result by extending the model presented in Heathcote, Storesletten, and Violante (2008) with a tax and transfer function of the Benabou or 'HSV' type. The progressivity parameter of this function is the theoretical counterpart of the state tax and transfer progressivity measure presented in Fleck, Heathcote, Storesletten, and Violante (2021). I then evaluate whether states in which I estimated higher risk aversion using Euler Equation approximations also have higher tax and transfer progressivity. I find empirical support for this relationship which provides additional evidence for the existence of sizable risk aversion differences across states.

6.1 Model Environment

My model environment has three essential features. First, agents are exposed to partially uninsurable earnings risk as wages are stochastic and asset markets are exogenously incomplete. Second, agents choose their labor supply endogenously and a higher marginal tax rate reduces their work effort. Thus, the model captures the key trade-off determining welfare effects of higher tax and transfer progressivity; it lowers uninsurable fluctuations in earnings, i.e. completes insurance markets, but reduces output generation as it discourages labor supply of workers with high earnings potential. Finally, contrary to the standard heterogeneous-agent incomplete-market framework, the model allows analytical solutions for equilibrium allocations. Hence, it yields tractable welfare comparisons of economies with different risk aversion and different progressivity.

A continuum of infinitely lived agents with measure one populates the economy. Agents value streams of consumption and hours worked according to

$$W = (1-\beta)E_0 \sum_{t=0}^{\infty} \beta^t u(c_t, h_t) \tag{19}$$

where $\beta < 1$ is the agent discount factor while c denotes consumption and h denotes hours worked. The period utility function is

$$u(c,h) = \frac{c^{1-\gamma}}{1-\gamma} - \frac{h^{1+\sigma}}{1+\sigma} \tag{20}$$

where γ is the coefficient of relative risk aversion and $\frac{1}{\sigma}$ the Frisch elasticity of the labor supply.

Output is generated using a production function with constant returns to scale which employs labor as its only input. Each agent's wage equals her productivity as labor and goods markets are perfectly competitive. Wages w are exogenous, stochastic and iid distributed across agents. In logs, they consist of the sum of two orthogonal components

$$\log w_t = \alpha + \varepsilon_t \tag{21}$$

where the agent fixed effect α is drawn before period 0 while ε_t is drawn in each period $t \geq 0$. Each component is distributed according to a Normal cumulative distribution function Φ_{v_α} (Φ_{v_ε}) with variance v_α (v_ε) and mean $-\frac{v_\alpha}{2}$ ($-\frac{v_\varepsilon}{2}$). Thus, log wages are distributed according to Φ_v with $v = v_\alpha + v_\varepsilon$.

Output cannot be stored but agents have access to one period Arrow securities which are in zero net supply and provide perfect insurance against transitory wage fluctuations but no insurance against permanent risk. Let b_{t-1} denote the gross return of a security purchased in $t-1$ while $p_t(\varepsilon')$ and $b_t(\varepsilon')$ define the price and quantity of securities which pay one unit of consumption in $t+1$ conditional in the realization of ε'. Thus, in every period, the budget constraint is given as

$$c_t + \int_E p_t(\varepsilon')b_t(\varepsilon')d(\varepsilon') = b_{t-1} + w_t h_t \tag{22}$$

Before time begins, i.e. when fixed effects are drawn, financial markets offer claims conditional on the realization of ε_0. As agents are born with zero financial wealth, their initial portfolio choice must satisfy

$$\int_E p_t(\varepsilon')b_t(\varepsilon')d(\varepsilon') = 0 \tag{23}$$

Equilibrium Properties In equilibrium, only agents with the same realization of the permanent shock α will trade Arrow securities as insurance against transitory shocks (but the prices of these securities do not depend on α).[27] Thus, solving the static social planner problem subject to a resource constraint for groups of agents with the same α provides competitive equilibrium allocations of consumption and hours worked for all agents. In logs, they are given as[28]

$$\log c(\alpha, \varepsilon) = \frac{1+\sigma}{\gamma+\sigma}\alpha + \frac{1+\sigma}{\gamma+\sigma}\frac{1}{\sigma}\frac{v_\varepsilon}{2} \tag{24}$$

$$\log h(\alpha, \varepsilon) = \frac{1-\gamma}{\gamma+\sigma}\alpha + \frac{1}{\sigma}\varepsilon - \frac{1+\sigma}{\gamma+\sigma}\frac{\gamma}{\sigma^2}\frac{v_\varepsilon}{2} \tag{25}$$

Thus, contrary to other models with incomplete markets and heterogeneous agents, keeping track of (current) realizations of labor productivity (α, ε) is sufficient to describe equilibrium allocations, i.e. individual asset holdings are no relevant state variable.[29]

The equilibrium allocations shown by equations (24) and (25) illustrate three key properties of this model; first, consumption does not depend on realizations of the transitory shock ε and responds to the permanent wage component according to the pass-through of α to hours worked.[30] Second, the response of hours worked to the transitory shock is governed by the Frisch elasticity while its response to the permanent component depends on the uncompensated elasticity; as long as $\gamma > 1$, it is decreasing in α as the income effect dominates the substitution effect. Third, consumption and leisure increase in the variance of the transitory earnings risk, v_ε.

6.2 Introducing Progressive Taxes

Suppose now that the economy features a tax function of the Benabou ('HSV') type. Its two parameters λ and τ regulate the relationship between earned income, $w_t h_t$ and disposable income $\tilde{y}$ according to

$$\tilde{y} = \lambda(w_t h_t)^{1-\tau} \tag{26}$$

where λ represents an average level of taxation while τ denotes the progressivity of the tax and transfer system. $\tau > 0$ indicates a progressive system while $\tau < 0$ reflects a regressive one. $\tau = 0$ represents a proportional system.

[27] See HSV 2007 appendix A for a formal proof of this model property.
[28] See appendix D.1 for the derivation.
[29] The reason is that, in equilibrium, net savings of agents with the same α are zero.
[30] To see this, note that $\log(wh) = \log(w) + \log(h)$ so the pass-through is $1 + \frac{1-\gamma}{\gamma+\sigma} = \frac{1+\sigma}{\gamma+\sigma}$.

Solving the Ramsey Problem In the presence of a tax and transfer system, finding equilibrium allocations associated with different degrees of tax progressivity (and, accordingly, different earnings variances) requires solving a Ramsey problem as differences in the marginal tax rates determine agents' labor supplies. To simplify notation, let the tax adjusted Frisch elasticity be defined as

$$\frac{1}{\hat{\sigma}} = \frac{1-\tau}{\sigma+\tau} \tag{27}$$

For agents with a particular realization of α, the social planner problem is given as[31]

$$\max_{c,h} \int_E u(c,h)\, d\Phi_{v_\varepsilon}(\varepsilon) \tag{28}$$

subject to the tax augmented resource constraint

$$\int_E \lambda(wh)^{1-\tau} - c\, d\Phi_{v_\varepsilon}(\varepsilon) = 0 \tag{29}$$

The agents first order conditions are given as

$$[c] \qquad c = \mu^{-\frac{1}{\gamma}} \tag{30}$$

$$[h] \quad h^{\sigma} = \mu\lambda w^{1-\tau}(1-\tau)h^{-\tau} \tag{31}$$

$$h = w^{\frac{1}{\hat{\sigma}}}\left[\mu\lambda(1-\tau)\right]^{\frac{1}{\sigma+\tau}} \tag{32}$$

Substituting the first order conditions into the resource constraint yields the multiplier μ as a function of the model primitives

$$\int_E \mu^{\frac{1}{\hat{\sigma}}}\lambda^{\frac{1+\hat{\sigma}}{\hat{\sigma}}}(1-\tau)^{\frac{1}{\hat{\sigma}}}(w^{1-\tau}w^{\frac{1-\tau}{\hat{\sigma}}}) - \mu^{-\frac{1}{\gamma}}\, d\Phi_{v_\varepsilon}(\varepsilon) = 0 \tag{33}$$

$$\lambda^{\frac{1+\hat{\sigma}}{\hat{\sigma}}}(1-\tau)^{\frac{1}{\hat{\sigma}}}\int_E w^{\frac{(1-\tau)(1+\hat{\sigma})}{\hat{\sigma}}}\, d\Phi_{v_\varepsilon} = \mu^{-\frac{1}{\gamma}-\frac{1}{\hat{\sigma}}} \tag{34}$$

Define $x = \frac{(1-\tau)(1+\hat{\sigma})}{\hat{\sigma}}$ so that

$$\lambda^{\frac{1+\hat{\sigma}}{\hat{\sigma}}}(1-\tau)^{\frac{1}{\hat{\sigma}}}\exp\left(\alpha x + x(x-1)\frac{v\varepsilon}{2}\right) = \mu^{-\left(\frac{1}{\gamma}+\frac{1}{\hat{\sigma}}\right)} \tag{35}$$

$$\left(\frac{1+\hat{\sigma}}{\hat{\sigma}}\right)\log(\lambda) + \frac{1}{\hat{\sigma}}\log(1-\tau) + \alpha x + x(x-1)\frac{v_\varepsilon}{2} = -\left(\frac{1}{\gamma}+\frac{1}{\hat{\sigma}}\right)\log(\mu) \tag{36}$$

$$\log(\mu) = -\frac{\gamma(1+\hat{\sigma})}{\gamma+\hat{\sigma}}\log(\lambda) - \frac{\gamma}{\gamma+\hat{\sigma}}\log(1-\tau) - \frac{\hat{\sigma}\gamma}{\gamma+\hat{\sigma}}\left(\alpha x + x(x-1)\frac{v_\varepsilon}{2}\right) \tag{37}$$

$$= -\frac{\gamma}{\gamma+\hat{\sigma}}\Big((1+\hat{\sigma})\log(\lambda) + \log(1-\tau)\Big) - \frac{\hat{\sigma}\gamma}{\gamma+\hat{\sigma}}\left(\alpha x + x(x-1)\frac{v_\varepsilon}{2}\right) \tag{38}$$

[31] For the ease of notation, I drop the arguments α and ε in the following exposition.

In levels, the multiplier μ is given as

$$\mu = \exp\Bigg(-\gamma\Bigg(\frac{\hat{\sigma}}{\hat{\sigma}+\gamma}\Bigg(\alpha x + x(x-1)\frac{v\varepsilon}{2}\Bigg)\Bigg) - \gamma\Bigg(\log\big(\lambda^{\frac{1+\hat{\sigma}}{\hat{\sigma}+\gamma}}(1-\tau)^{\frac{1}{\hat{\sigma}+\gamma}}\big)\Bigg)\Bigg)$$

$$= \frac{\exp\Big(-\gamma\Big(\frac{\hat{\sigma}}{\hat{\sigma}+\gamma}\Big(\alpha x + x(x-1)\frac{v\varepsilon}{2}\Big)\Big)\Big)}{\Big(\lambda^{\frac{1+\hat{\sigma}}{\hat{\sigma}+\gamma}}(1-\tau)^{\frac{1}{\hat{\sigma}+\gamma}}\Big)^{\gamma}} \tag{39}$$

$$= \exp\Bigg(-\gamma\Bigg(\frac{\hat{\sigma}}{\hat{\sigma}+\gamma}\Bigg(\alpha x + x(x-1)\frac{v\varepsilon}{2}\Bigg)\Bigg)\Bigg(\lambda^{-\frac{\gamma(1+\hat{\sigma})}{\hat{\sigma}+\gamma}}(1-\tau)^{-\frac{\gamma}{\hat{\sigma}+\gamma}}\Bigg) \tag{40}$$

To find the equilibrium allocations in the economy with taxes, I substitute the multiplier μ of equation (38) into the first order conditions. (Log) consumption is given as

$$\log c = -\frac{1}{\gamma}\log(\mu) \tag{41}$$

$$= -\frac{1}{\gamma}\Bigg(-\frac{\hat{\sigma}\gamma}{\gamma+\hat{\sigma}}\Bigg(\alpha x + x(x-1)\frac{v_\varepsilon}{2}\Bigg) \tag{42}$$

$$- \frac{\gamma}{\gamma+\hat{\sigma}}\Bigg((1+\hat{\sigma})\log(\lambda) + \log(1-\tau)\Bigg)\Bigg)$$

$$= \frac{\hat{\sigma}}{\gamma+\hat{\sigma}}x\alpha + \frac{\hat{\sigma}}{\gamma+\hat{\sigma}}x(x-1)\frac{v_\varepsilon}{2} \tag{43}$$

$$+ \frac{1}{\gamma+\hat{\sigma}}\Bigg((1+\hat{\sigma})\log(\lambda) + \log(1-\tau)\Bigg)$$

$$= \frac{(1-\tau)(1+\hat{\sigma})}{\gamma+\hat{\sigma}}\alpha + \frac{(1-\tau)(1+\hat{\sigma})}{\gamma+\hat{\sigma}}(1-\tau(1+\hat{\sigma}))\frac{1}{\hat{\sigma}}\frac{v_\varepsilon}{2} \tag{44}$$

$$+ \frac{1}{\gamma+\hat{\sigma}}\Bigg(\log\Big(\lambda^{1+\hat{\sigma}}(1-\tau)\Big)\Bigg)$$

$$= \frac{(1-\tau)(1+\hat{\sigma})}{\gamma+\hat{\sigma}}\alpha + \frac{(1-\tau)(1+\hat{\sigma})}{\gamma+\hat{\sigma}}(1-\tau(1+\hat{\sigma}))\frac{1}{\hat{\sigma}}\frac{v_\varepsilon}{2} + \kappa_c \tag{45}$$

where $\kappa_c = \frac{1}{\gamma+\hat{\sigma}}\Bigg(\log\Big(\lambda^{1+\hat{\sigma}}(1-\tau)\Big)\Bigg)$.

(Log) labor is given as

$$\log h = \frac{1}{\hat{\sigma}(1-\tau)}\log(\mu) + \frac{\alpha+\varepsilon}{\hat{\sigma}} + \frac{1}{\hat{\sigma}(1-\tau)}\Big(\log(\lambda) + \log(1-\tau)\Big) \tag{46}$$

$$= \frac{1}{\hat{\sigma}(1-\tau)}\Bigg(-\frac{\gamma}{\gamma+\hat{\sigma}}\Bigg((1+\hat{\sigma})\log(\lambda) + \log(1-\tau)\Bigg) - \frac{\hat{\sigma}\gamma}{\gamma+\hat{\sigma}}\Bigg(\alpha x + x(x-1)\frac{v_\varepsilon}{2}\Bigg)\Bigg)$$

$$+ \frac{\alpha+\varepsilon}{\hat{\sigma}} + \frac{1}{\hat{\sigma}(1-\tau)}\Big(\log(\lambda) + \log(1-\tau)\Big)$$

$$= \left(\frac{1}{\hat{\sigma}} - \frac{\gamma}{\hat{\sigma}(1-\tau)}\frac{(1-\tau)(1+\hat{\sigma})}{\hat{\sigma}+\gamma}\right)\alpha + \frac{1}{\hat{\sigma}}\varepsilon \tag{47}$$

$$- \frac{\gamma}{\hat{\sigma}+\gamma}\frac{1+\hat{\sigma}}{\hat{\sigma}}\left(\frac{(1-\tau)(1+\hat{\sigma})}{\hat{\sigma}} - 1\right)\frac{v_\varepsilon}{2}$$

$$- \frac{1}{1-\tau}\left(\log\left(\lambda^{\frac{1-\gamma}{\gamma+\hat{\sigma}}}(1-\tau)^{\frac{1}{\gamma+\hat{\sigma}}}\right)\right) \tag{48}$$

$$= \left(\frac{1-\gamma}{\gamma+\hat{\sigma}}\right)\alpha + \frac{1}{\hat{\sigma}}\varepsilon - \frac{1+\hat{\sigma}}{\gamma+\hat{\sigma}}(1-\tau(1+\hat{\sigma}))\frac{\gamma}{\hat{\sigma}^2}\frac{v_\varepsilon}{2} - \kappa_h \tag{49}$$

where $\kappa_h = \frac{1}{(1-\tau)(\gamma+\hat{\sigma})}\left(\log\left(\lambda^{1-\gamma}(1-\tau)\right)\right)$.

Thus, collecting terms shows that the equilibrium (Ramsey) allocations are log linear in α and current realizations of ε as well as model primitives

$$\log c = \frac{(1-\tau)(1+\hat{\sigma})}{\gamma+\hat{\sigma}}\alpha + \frac{(1-\tau)(1+\hat{\sigma})}{\gamma+\hat{\sigma}}(1-\tau(1+\hat{\sigma}))\frac{1}{\hat{\sigma}}\frac{v_\varepsilon}{2} + \kappa_c(\sigma,\gamma,\lambda,\tau)$$

$$\log h = \left(\frac{1-\gamma}{\gamma+\hat{\sigma}}\right)\alpha + \frac{1}{\hat{\sigma}}\varepsilon - \frac{1+\hat{\sigma}}{\gamma+\hat{\sigma}}(1-\tau(1+\hat{\sigma}))\frac{\gamma}{\hat{\sigma}^2}\frac{v_\varepsilon}{2} + \kappa_h(\sigma,\gamma,\lambda,\tau)$$

Discussion First, as expected, in the case of zero progressivity, i.e. if $\tau = 0$ (so $\hat{\sigma} = \sigma$), the equilibrium allocations given in equations (45) and (49) collapse to those of the no tax economy shown in equations (24) and (25). Second, as progressivity approaches full redistribution, equilibrium consumption falls to zero. To see this, note that the factors of α and $\frac{v_\varepsilon}{2}$ approach zero as τ goes to one and $\lim_{\tau\to 1}\kappa_c = -\infty$ which means that $\lim_{\tau\to 1}\exp(\kappa_c) = 0$ so $\lim_{\tau\to 1} c = 0$. The reason is that, with full redistribution, labor supply falls to zero so there is no more output to consume. Third, for values of progressivity $0 < \tau < 1$, consumption is still determined by the permanent risk component (α) and the mean of the transitory component ($\frac{v_\varepsilon}{2}$). However, all factors now include the tax progressivity term $(1-\tau)$ and the tax adjusted Frisch elasticity $\hat{\sigma}$. Thus, in addition to σ and γ, these parameters determine the consumption response. This is also true for the labor response; it is still determined by realizations of both risk components as well as the mean of the transitory component. However, as consumption, it is now also determined by τ (and $\hat{\sigma}$).

Finally, both equilibrium allocations also depend on λ which is the implicit average tax rate of the HSV tax function. The reason is that, for a given τ there is a unique value of λ such at that the tax and transfer system respects the aggregate resource constraint, i.e. equates aggregate consumption to total production. Thus, it can be computed as a function of all model primitives. See appendix D.2 for a full exposition of this computation.

Parameter	Value	Source
σ	2	Standard
v_α	0.22	Heathcote, Storesletten, and Violante (2008)
v_ε	0.13	Heathcote, Storesletten, and Violante (2008)
γ	$\{1.97, 2.21, 2.35\}$	See section 4

Table 8: *Parameters for the Welfare Comparison of Tax Progressivity when Risk Aversion (γ) differs.*

6.3 Optimal Progressivity for Different Values of Risk Aversion

The Social Planner Choice Suppose that a social planner chooses the optimal value of tax progressivity, τ^*. Her objective is to maximize social welfare assuming equal Pareto weights for all agents in the economy. While the model does not allow a closed-form solution to compute optimal progressivity, it does provide tractable welfare comparisons for different values of τ. To see this, note that, as w reflects the variances of permanent and transitory risk, values of $\tau > 0$ reduce the variability of disposable income with respect to both variances v_α and v_ε.[32] Let a specific choice of the progressivity parameter, $\hat{\tau}$, reduce the variances of permanent and transitory shocks from v_α and v_ε to $\hat{v}_\alpha$ and $\hat{v}_\varepsilon$. In units of equivalent compensating variation, the welfare change ω associated with these reductions can be computed as

$$\begin{aligned} &\int_A \int_E u((1+\omega)c(\alpha,\varepsilon), h(\alpha,\varepsilon) d\Phi_{v_\varepsilon}(\varepsilon) d\Phi_{v_\alpha}(\alpha) \\ &\qquad = \int_A \int_E u(\hat{c}(\alpha,\varepsilon), \hat{h}(\alpha,\varepsilon) d\Phi_{\hat{v}_\varepsilon}(\varepsilon) d\Phi_{\hat{v}_\alpha}(\alpha) \end{aligned} \tag{50}$$

where $\hat{c}(\alpha,\varepsilon)$ and $\hat{h}(\alpha,\varepsilon)$ are the equilibrium allocations at the lower values of permanent and transitory earnings risk.

Figure 4 shows the welfare effects of different values for tax progressivity, τ. As shown in table 8, this computation uses the three different values of risk aversion computed in section 4 and a common set of values for the Frisch elasticity and the variances of the earnings risk components. Lower values of tax progressivity result in a lower reduction of earnings risk. However, they are also associated with lower distortions on labor supply decisions. Thus, they result in higher output generation. As τ increases, disposable earnings risk falls – as does output.

[32] For $\tau = 1$, full wage compression results as the variances v_ε and v_α collapse to zero.

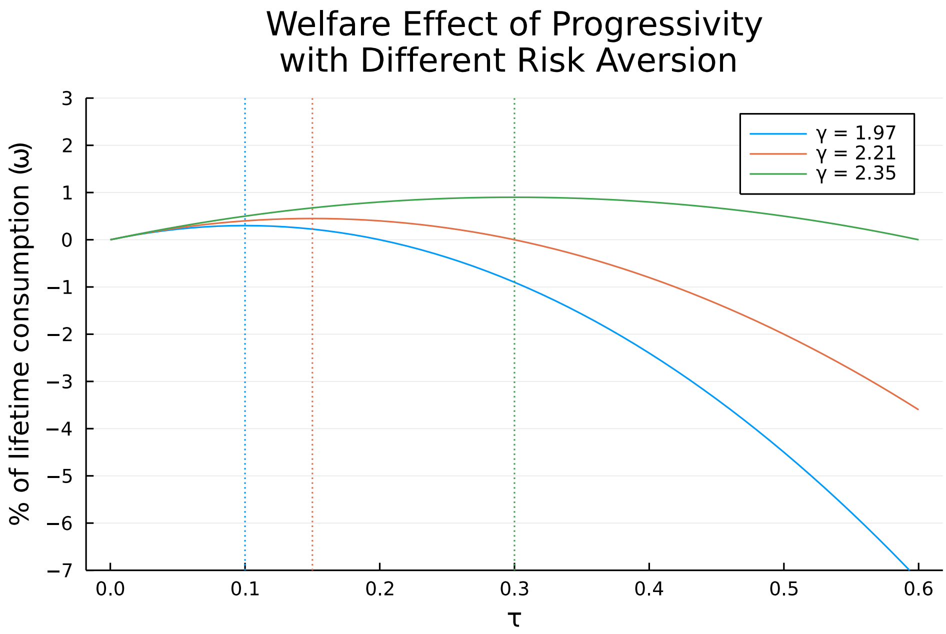

Figure 4: *Welfare Effect of Different Tax Progressivity τ in Economies with Different Risk Aversion γ*

For a range of progressivity values, figure 4 illustrates the net welfare change of both of these effects for economies with different values of the risk aversion parameter γ. The figure illustrates two results. First, independent of risk aversion, welfare is concave in tax progressivity. This finding reflects that, at low values of progressivity, the welfare gain from completing markets dominates the welfare loss from depressing labor supply. For high values of progressivity, this relationship is reversed. Second, welfare-maximizing progressivity is increasing in risk aversion. To see this, note that for a low value of risk aversion, $\gamma = 1.97$, the maximum increase in life-time consumption (0.3%) provided by progressive taxation results at a value of $\tau^*_{\gamma=1.97} = 0.01$. For the largest value of risk aversion, this value is $\tau^*_{\gamma=2.35} = 0.03$ which corresponds to a welfare increase of about 1%.

Thus, the key insight from the model is that risk aversion is a key determinant of a benevolent social planner's tax progressivity choice; ceteris paribus, larger risk aversion calls for higher progressivity. For that reason, cross-state differences in risk aversion are a natural candidate explaining differences in cross-state tax and transfer progressivity.

The Political Economy Determination Suppose now that the choice on τ^* is determined by once-and-for-all voting. Note that the transitory shock, ε, can be fully insured privately so the only dimension which determines heterogenous views on optimal progressivity is the distribution of permanent shocks, α. Given the assumption on the distribution of α, the median agent has a realization of $\alpha^* = -\frac{v_\alpha}{2}$.

To show that the median voter theorem applies in this economy, recall that equilibrium (Ramsey) allocations of consumption and hours worked are log linear. Thus, substituting them into the agent utility function allows to represent tractable welfare expressions W which are functions only of the realizations of α and ε as well as model primitives. It can be shown that the welfare of the median voter is monotonically decreasing in the permanent shock $\frac{\partial W(\alpha^*)}{\partial \tau} < 0$. Hence, the median voter theorem applies as preferences are monotone over different values of tau – the larger the permanent productivity realization, the lower the support for more insurance and redistribution via tax progressivity.

Moreover, it can be shown that the value of tax progressivity desired by the median voter, τ^*, increases in risk aversion. To see this, rewrite the optimality condition $\frac{\partial W(\alpha^*)}{\partial \tau} = 0$ as $F(\tau, \gamma) = 0$. Taking the total derivative of this expression with respect to γ shows that

$$-\underbrace{\frac{F_\gamma}{F_\tau}}_{<0} = \underbrace{\frac{d\tau}{d\gamma}}_{>0} \tag{51}$$

Thus, the degree of tax progressivity desired by the median voter increases in risk aversion. The intuition behind this finding is that the value of consumption insurance provided by tax and transfer progressivity is increasing in risk aversion; more risk averse median voters prefer higher tax progressivity as it insures against the possibility to have low realizations of permanent productivity. The gain of this insurance effect outweighs the loss of output and income due to the negative effect of higher marginal taxes on labor supply.

The Empirical Relationship between State-level Risk Aversion and Tax Progressivity Both the social planner and the political economy determination of tax progressivity unambiguously predict a positive association between risk aversion and tax and transfer progressivity. Hence, a natural way to provide auxiliary evidence on differences in risk aversion across states is to study the cross-state variation in tax and transfer progressivity and relate it to the estimates of risk aversion I presented in section 4.

In order to characterize differences in state tax and transfer progressivity, I use the empirical measure presented in Fleck, Heathcote, Storesletten, and Violante (2021). Their measure is the empirical counterpart to the parameter τ in the model presented above. For each state, they compute the progressivity of a rich set of state taxes and transfers, see table 17 in appendix E.1 for details.

To evaluate the relationship between state progressivity and the findings on risk aversion, figure 5 orders states from least progressive (left) to most progressive (right). States which are in the group of the ten states with the lowest estimates of risk aversion are highlighted in dark green while those ten with the lowest risk aversion estimates are highlighted in light green. As this figure illustrates, there is a clear positive association between risk aversion and state tax and transfer progressivity; states which are more risk averse tend to be at the upper end of the progressivity spectrum. The opposite applies to states which are less risk averse – they rank low in the distribution of tax and transfer progressivity.

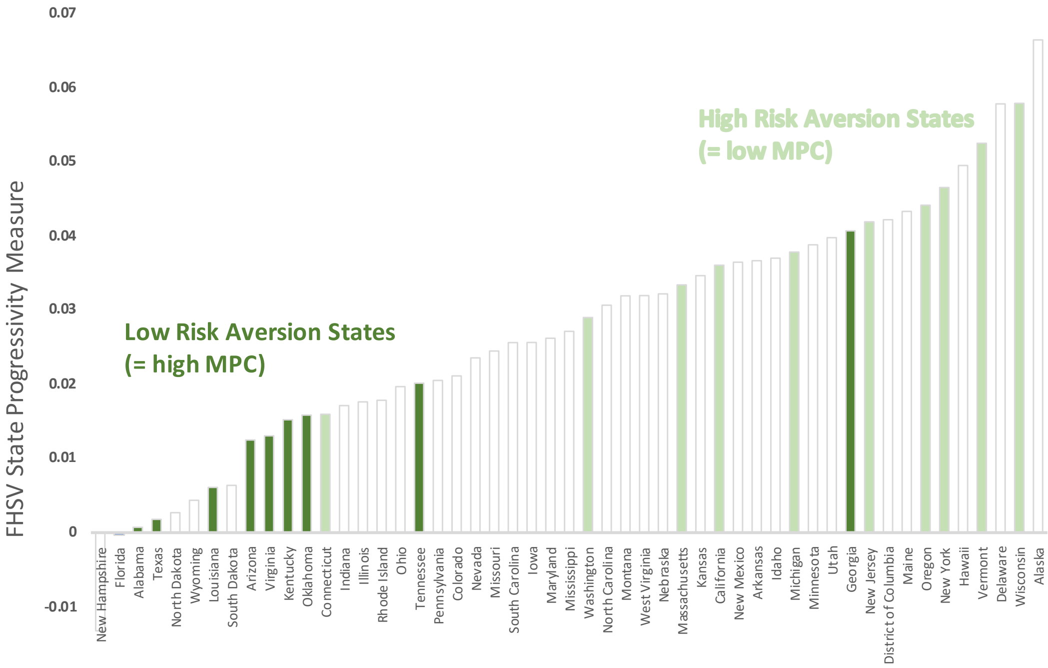

Figure 5: *The relationship between estimated risk aversion and state tax and transfer progressivity. Low risk averse states in dark green, high risk averse states in light green. States are ranked according to the progressivity measure of Fleck, Heathcote, Storesletten, and Violante (2021).*

7 Other Drivers of Cross-State MPC Differences

In section 5, I demonstrated that accounting for state differences in risk aversion aligns the theoretical predictions on cross-state MPC differences with the empirical evidence. However, even though the share of the explained variation increases substantially, introducing state specific risk aversion does not fully explain cross-state MPC variation. Which other state characteristics could explain additional variation in regional MPCs? Guided by the model presented in section 5, I now investigate the role of three additional state characteristics.

7.1 State Tax and Transfer Progressivity

In the preceding section, I found that states differ with respect to the progressivity of their tax and transfer policies. Can these policy differences explain variation in cross-state MPCs? To answer this question, I extend the model presented in section 5 by introducing tax and transfer heterogeneity as another dimension of regional heterogeneity. I do so by adding a government sector.

Government The government operates a tax and transfer system of the HSV type. Thus, household disposable income is given as

$$y^d_{i,t} = \lambda y_{i,t}^{1-\tau} \tag{52}$$

so households can consume or save arbitrary amounts c_t and b_t of $y^d_{i,t}$ (not $y_{i,t}$). The government does not pursue any distributional objectives and is completely defined by its tax function's two exogenous parameters, λ and τ. It spends any excess revenues on wasteful activities. The tax and transfer parameters determine two properties of individual (and average) MPCs in this model:

Proposition 1: Higher progressivity reduces disposable income risk which lowers precautionary motives Let Y^d denote the distribution of disposable income and Y the distribution of earned income. After taking logs on both sides of equation (52), their variances are given as

$$\sigma^2\big(\log(Y^d)\big) = (1-\tau)^2\sigma^2\big(\log(Y)\big) \tag{53}$$

Thus, the value of τ regulates the pass through of shocks from earned to disposable income. If the system is proportional ($\tau = 0$) it is neutral in this regard while larger values of τ lower the variability of disposable income and negative values exacerbate it. Figure 6 summarizes this relationship.

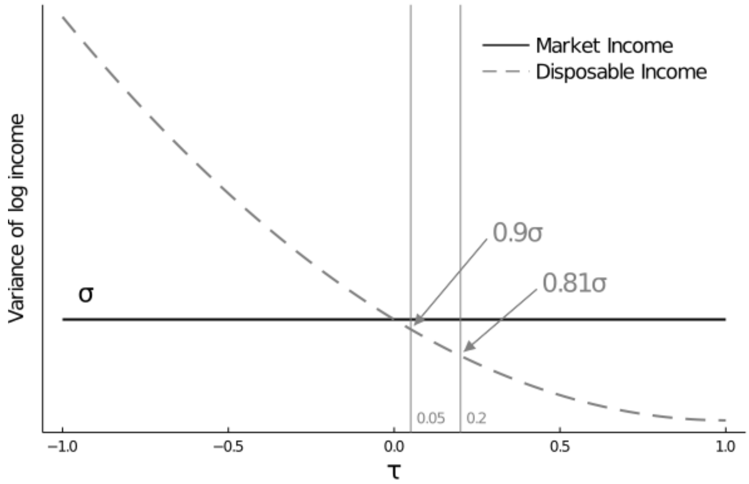

Figure 6: *The effect of progressive taxes on the variability of disposable income.*

Thus, for a given variability of earned income, the variability of disposable income is lower in states with higher progressivity. In other words, progressivity alleviates the incompleteness of asset markets and provides insurance against fluctuations in disposable income. Accordingly, households in state economies with higher progressivity have a lower level of desired precautionary savings.

Proposition 2: Progressivity only affects MPCs of households with low levels of wealth In canonical consumption savings models with incomplete markets, the consumption function is increasing and concave in liquid wealth. However, the consumption behavior of households who have accumulated high levels of liquid wealth is isomorphic to an economy without uncertainty and liquidity constraints. This is because at high levels of liquid wealth, households are fully insured against undesirable consumption fluctuations due to current low realizations of income. The marginal propensity to consume transitory income of these households is $1-\beta$, i.e. linear. Hence, it is independent of the degree of tax progressivity.

To see this, note that in the certainty case, the model collapses to the representative agent framework. This model's Euler Equation is given as

$$c_t^{-\gamma} = (1+\bar{r})\beta c_{t+1}^{-\gamma} \tag{54}$$

$$c_{t+1} = \big((1+\bar{r})\beta\big)^{1/\gamma} c_t \tag{55}$$

The MPC of this economy can be found by iterating the budget constraint over subsequent periods

$$c_t + a_{t+1} = (1+\bar{r})a_t + \lambda y_t^{(1-\tau)} \tag{56}$$

$$c_{t+1} + a_{t+2} = (1+\bar{r})a_{t+1} + \lambda y_{t+1}^{(1-\tau)} \tag{57}$$

$$\dots$$

Repeatedly inserting a_{t+n} results in

$$c_0 + \frac{c_1}{1+\bar{r}} + \frac{c_2}{1+\bar{r}} + \ldots = (1+\bar{r})a_0 + \lambda y_0^{(1-\tau)} + \frac{\lambda y_1^{(1-\tau)}}{(1+\bar{r})} + \frac{\lambda y_2^{(1-\tau)}}{(1+\bar{r})^2} \tag{58}$$

$$= (1+\bar{r})a_0 + \sum_{t=0}^{\infty}\left(\frac{1}{1+\bar{r}}\right)^t \lambda y_t^{(1-\tau)} \tag{59}$$

Linking terms on the left hand side using the Euler equation (55) and expressing consumption in terms of period 0 leads to

$$c_0\left(\frac{1}{1-\left(\beta(1+\bar{r})\right)^{1/\gamma}(1+\bar{r})^{-1}}\right) = (1+\bar{r})a_0 + \sum_{t=0}^{\infty}\left(\frac{1}{1+\bar{r}}\right)^t \lambda y_t^{(1-\tau)} \tag{60}$$

so that

$$c_0 = \underbrace{\left(1 - \frac{\left(\beta(1+\bar{r})\right)^{1/\gamma}}{(1+\bar{r})}\right)}_{mpc}\left(\underbrace{(1+\bar{r})a_0}_{\text{Asset Endowment}} + \underbrace{\lambda\sum_{t=0}^{\infty}\left(\frac{1}{1+\bar{r}}\right)^t y_t^{(1-\tau)}}_{\text{Disposable Income Endowment}}\right) \tag{61}$$

which illustrates that the MPC is linear in the sum of the endowments of assets and disposable incomes. For example, for the case of $\gamma = 1$ and $a_0 = 0$, it becomes

$$c^* = \underbrace{(1-\beta)}_{mpc}\ \underbrace{\lambda\sum_{t=0}^{\infty}\left(\frac{1}{1+\bar{r}}\right)^t y_t^{(1-\tau)}}_{\text{Disposable Income Endowment}} \tag{62}$$

Even in the model with uncertainty, the MPC will converge to this certainty case as households accumulate more wealth. Hence, for households with high levels of liquid wealth, the MPC is solely determined by the rate of time preference β and independent of the tax function parameters, τ and λ. However, the consumption function (c^*) remains determined by λ, i.e. the average level of taxation in the economy; larger average taxes reduce the value of the disposable income endowment and reduce (average) consumption expenditures.

Parameter	Value	Description	Target/Source
τ		Tax and Transfer Progressivity	
federal	0.2		Fleck, Heathcote, Storesletten, and Violante (2021)
low risk state	0.179		Fleck, Heathcote, Storesletten, and Violante (2021)
high risk state	0.216		Fleck, Heathcote, Storesletten, and Violante (2021)
g		Public Revenue Share	(used to calibrate λ federal, low and high, see eq. 64)
federal	0.15		Census Bureau
low risk state	0.18		Census Bureau
high risk state	0.21		Census Bureau

Table 9: *Calibration of the federal, high risk and low risk progressivity models.*

Calibrating the Tax Parameters I calibrate the parameters of the tax function using the *federal* progressivity reported by Fleck, Heathcote, Storesletten, and Violante (2021), $\tau^f = 0.2$. To compute the associated λ^f, I inspect data on the federal tax revenue relative to national GDP in 2001 (g^f = 15%). Total income in the model economy $\overline{Y}$ is constant, i.e. independent of the tax function parameters. Thus, for given values of τ and g, λ can be computed as

$$g\overline{Y} = \overline{Y} - \lambda\overline{Y}^{1-\tau} \tag{63}$$

$$\lambda = (1-g)\overline{Y}^{-\frac{1}{\tau}} \tag{64}$$

To investigate the effect of tax and transfer progressivity on state average MPCs, I retain the same value for β as before but change the calibration of the tax function using the numerical estimates for $\tau^{s,high}$ and $\tau^{s,low}$ reported by Fleck, Heathcote, Storesletten, and Violante (2021). I proceed analogously for the state average tax, i.e. I collect revenue shares of states with high and low tax and transfer progressivity (see figure 15 in appendix E.6). Table 9 lists the complete set of parameter choices related to tax and transfer progressivity.

Results Figure 7 shows the consumption functions for all three calibrations of the model, i.e. reflecting the progressivity of federal taxes and transfers as well as the highest and lowest state progressivity. The left panel shows that, for high levels of liquid wealth, the consumption functions have a uniform slope, consistent with the theoretical result derived in the preceding section; for households with high levels of liquid wealth, the MPC is unaffected by tax progressivity. (As states with high tax progressivity tend to have larger levels of average taxes, the consumption function of the high progressivity calibration is lower due to a larger value of λ.)

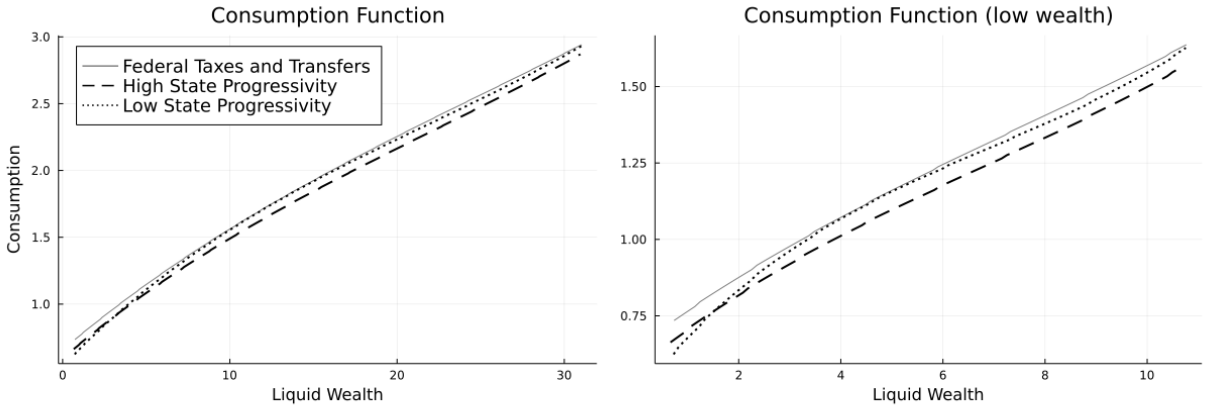

Figure 7: *Consumption Functions of the federal, high state progressivity and low state progressivity models. Left panel: all wealth levels. Right panel: low wealth levels.*

The right panel of figure 7 displays the consumption functions for low levels of wealth, where MPCs are not linear. The slope of these functions illustrates two effects of differences in state tax and transfer progressivity; lower progressivity concavifies the consumption function – the MPC for the less progressive calibration is always larger than in the case of more progressivity, in particular at low levels of liquid wealth. The reason is that higher progressivity absorbs a larger share of shocks to disposable income, i.e. it provides more insurance against fluctuations in consumable income. This effect makes the consumption behavior converge to the certainty case (constant MPC equal to 1-β) at all levels of wealth.

However, the low progressivity calibration also implies that a smaller mass of households is close to or at the borrowing constraint in the stationary distribution. As the utility function of this model features prudence, the demand for liquid assets due to precautionary reasons is larger. As a result, fewer households are at the steeper parts of the consumption function. This effect offsets the impact of stronger concavity on the average MPC in the less progressive economy.

Table 10 shows the average MPC in the low and high risk aversion states. In addition to the results reported earlier, it also includes average MPCs when introducing differences in tax and transfer progressivity between the low and high risk aversion states. As the first column of this table shows, the effect of progressivity differences on MPCs are much smaller from a quantitative point of view than the risk aversion differences; they lead to marginally larger average MPCs in both state groups. The reason is because they reduce financial precautionary behavior in both state groups. As a result, the share of hand-to-mouth households increases, but only by a very small amount.

	Average MPC		Mean liquid wealth/mean income		Hand-to-mouth (htm, %)	
	Model	Estimate	Model	Data	Model	Data
Low Risk Aversion State	0.31	0.53	0.45	0.41[3]	17.3	12.1[3]
+ Low Progressivity	0.32		0.44		17.5	
High Risk Aversion State	0.15	<0.18	0.60	0.49[3]	10.0	8.4[3]
+ High Progressivity	0.17		0.58		10.3	

Table 10: *Model Results of the High and Low Risk Aversion Calibration Including State Tax and Transfer Progressivity.* [3]*Constructed from IRS tax return data.*

In summary, compared to the effect of cross-state risk aversion differences, discrepancies in the progressivity of state fiscal policies only play a minor quantitative role in determining regional MPCs.

7.2 Earnings Risk

State specific earnings risk, i.e. regional variability in ρ^s and $\sigma_\eta^{2,s}$ could determine regional differences in MPCs through its effect on the financial precautionary behavior of households. In fact, some studies argue that the exposure to persistent earning shocks is concentrated in a few (Rust-Belt) US states. One of the leading examples of this view is Autor, Dorn, Hanson, and Song (2014) who argue that the decline of American manufacturing and union membership has resulted in highly persistent earnings risk in certain geographic areas. Thus, in an earnings process with a transitory and persistent component, states would differ in the error variances. As the consumption function is defined for a particular process for income, introducing cross-state variation in earning risk has direct consequences for the state average MPC.[33]

To investigate if households in high and low MPC states are exposed to more (or less) persistent earning shocks, I leverage the fact that the ASEC dataset has a panel component which is short in the longitudinal dimension but rich in the cross-section. I use it to estimate state specific error variances of an earnings process with transitory and persistent risk given as

$$\tilde{y}_{i,t,s} = z_{i,t,s} + \varepsilon_{i,t,s} \sim N(0, \sigma^2_{\varepsilon,s}) \tag{65}$$

$$z_{i,t,s} = \rho z_{i,t-1,s} + \eta_{i,t,s} \sim N(0, \sigma^2_{\eta,s}) \tag{66}$$

where $\tilde{y}_{i,t,s}$ denote unpredictable earnings of unit i in state s in period t and ρ, $\sigma^2_{\varepsilon,s}$ and $\sigma^2_{\eta,s}$ are exogenous parameters.

[33] Crawley and Kuchler (2020) study differences in MPCs out of transitory and permanent earning shocks.

Proposition: For a given value of the persistence parameter, $\overline{\rho}$, the error variances of this earnings process can be estimated for each state using the following moments of a two-period panel $(T = 2, N = large)$

$$\hat{\sigma}^2_{\varepsilon,s} = \hat{var}(y_{i,t,s}) - \frac{1}{\overline{\rho}}\, \hat{cov}(y_{i,t,s}, y_{i,t-1,s}) \tag{67}$$

$$\hat{\sigma}^2_{\eta,s} = \hat{var}(\Delta y_{i,t,s}) - 2\hat{var}(y_{i,t}) + \left(\frac{1-\overline{\rho}^2}{\overline{\rho}} + 2\right)\hat{cov}(y_{i,t}, y_{i,t-1}) \tag{68}$$

Proof:

The transitory and persistent error variances are assumed to be distributed according to

$$\varepsilon_{i,t} \overset{iid}{\sim} N(0, \sigma^2_\varepsilon) \tag{69}$$

$$\eta_{i,t} \overset{iid}{\sim} N(0, \sigma^2_\eta) \tag{70}$$

This assumption implies that

$$\mathbb{E}[y_{i,t}] = \mathbb{E}[z_{i,t}] = 0 \tag{71}$$

$$var(y_{i,t}) = \mathbb{E}[y^2_{i,t}] \tag{72}$$

$$var(z_{i,t}) = \mathbb{E}[z^2_{i,t}] \tag{73}$$

Using (65) and (70) it is straightforward to show that

$$\sigma^2_\varepsilon = var(y_{i,t}) - var(z_{i,t}) \tag{74}$$

Note that

$$var(z_{i,t-1}) = \frac{1}{\overline{\rho}}\, cov(y_{i,t}, y_{i,t-1}) \tag{75}$$

which can be seen from expanding $cov(y_{i,t}, y_{i,t-1})$ as follows

$$cov(y_{i,t}, y_{i,t-1}) = \mathbb{E}[y_{i,t}y_{i,t-1}] - \underbrace{\mathbb{E}[y_{i,t}]\mathbb{E}[y_{i,t-1}]}_{=0} \tag{76}$$

$$= \mathbb{E}[(z_{i,t} + \varepsilon_{i,t})(z_{i,t-1} + \varepsilon_{i,t-1})] \tag{77}$$

$$= \mathbb{E}[z_{i,t}z_{i,t-1}] + \underbrace{\mathbb{E}[z_{i,t}\varepsilon_{i,t-1}]}_{=0} + \underbrace{\mathbb{E}[\varepsilon_{i,t}z_{i,t-1}]}_{=0} + \underbrace{\mathbb{E}[\varepsilon_{i,t}\varepsilon_{i,t-1}]}_{=0} \tag{78}$$

$$= cov(z_{i,t}, z_{i,t-1}) \tag{79}$$

$$= cov(\overline{\rho} z_{i,t-1} + \eta_{i,t}, z_{i,t-1}) \tag{80}$$

$$= \bar{\rho}\; cov(z_{i,t-1}, z_{i,t-1}) \tag{81}$$

$$= \bar{\rho}\; var(z_{i,t-1}) \tag{82}$$

Hence, combining (74) and (75) gives the variance of the transitory innovation as

$$\sigma_\varepsilon^2 = var(y_{i,t}) - \frac{1}{\bar{\rho}}\, cov(y_{i,t}, y_{i,t-1}) \tag{83}$$

Next, turning to the variance of the persistent innovation, let $\Delta y_{i,t} = y_{i,t} - y_{i,t-1}$ so that

$$\Delta y_{i,t} = z_{i,t} + \varepsilon_{i,t} - \left(z_{i,t-1} + \varepsilon_{i,t-1}\right) \tag{84}$$

$$= z_{i,t} - z_{i,t-1} + \varepsilon_{i,t} - \varepsilon_{i,t-1} \tag{85}$$

$$= \bar{\rho} z_{i,t-1} + \eta_{i,t} - z_{i,t-1} + \varepsilon_{i,t} - \varepsilon_{i,t-1} \tag{86}$$

$$= (\bar{\rho} - 1) z_{i,t-1} + \eta_{i,t} + \varepsilon_{i,t} - \varepsilon_{i,t-1} \tag{87}$$

The variance of this expression is given as

$$var(\Delta y_{i,t}) = (\bar{\rho} - 1)^2\, var(z_{i,t-1}) + \sigma_\eta^2 + 2\sigma_\varepsilon^2 \tag{88}$$

so the variance of the persistent innovation is given as

$$\sigma_\eta^2 = var(\Delta y_{i,t}) - (\bar{\rho} - 1)^2\, var(z_{i,t-1}) - 2\sigma_\varepsilon^2 \tag{89}$$

$$= var(\Delta y_{i,t}) - (\bar{\rho} - 1)^2\, \frac{1}{\bar{\rho}}\, cov(y_{i,t}, y_{i,t-1}) - 2\left(var(y_{i,t}) - \frac{1}{\bar{\rho}}\, cov(y_{i,t}, y_{i,t-1})\right) \tag{90}$$

$$= var(\Delta y_{i,t}) - 2 var(y_{i,t}) + \left(\frac{1 - \bar{\rho}^2}{\bar{\rho}} + 2\right) cov(y_{i,t}, y_{i,t-1}) \tag{91}$$

where results from above have been used to substitute terms on the right hand side. In summary, as equations (83) and (91) show, with a panel of $T = 2$, the two parameters σ_ε^2 and σ_η^2 can be estimated using the two data moments $var(\Delta y_{i,t})$, $cov(y_{i,t}, y_{i,t-1})$ and $var(\Delta y_{i,t})$.

Appendix F provides details on my estimation and figure 17 presents the estimates of the transitory and persistent innovation variances for each state. I investigate the relationship of each of these measures of earnings risk with state tax and transfer progressivity in an OLS regression where I specify the measure of Fleck, Heathcote, Storesletten, and Violante (2021) for state tax and transfer progressivity presented as the dependent variable. My findings are presented in columns (1) and (2) of table 11.

Both of the point estimates are not statistically different from zero, even at a low level of statistical significance. This finding demonstrates that differences in earnings risk do not correlate with state tax and transfer progressivity and risk aversion. Therefore, this dimension of cross-state heterogeneity cannot confound the role of state taxes and transfers in determining state average MPCs. Moreover, it is not a suitable candidate to align theoretical predictions on cross-state differences in MPCs with the empirical evidence.[34]

7.3 Minimum Wages and Consumer Credit Markets

To investigate the relationship between state minimum wages and state tax and transfer progressivity, I collect data on state minimum wages for the period 2000 to 2008.During this period, 14 states had state minimum wages exceeding the federal minimum wage. I regress the state average minimum wage on the state measure of state tax and transfer progressivity and present the results in column (3) of table 11. The coefficient estimate is small in magnitude and statistically insignificant. This evidence speaks against the possibility that state minimum wages co-determine differences in state average MPCs in addition to differences in tax and transfer progressivity and risk aversion.

The empirical household finance literature provides robust evidence on regional differences in the availability and cost of consumer credits, especially in the supply of unsecured consumer credit.[35] For example, interest rates on consumer loans and credit card debt have been shown to vary across states, especially before the arrival of internet banking. Most of these differences are attributable to state regulation regarding bank branching within states and the ease of entry for non-state banks.

According to this literature, equally relevant determinants of the access to and cost of consumer credits are state regulations regarding the relationship between debtors and creditors in case of default. For example, states have different rules regarding wage garnishment of delinquent borrowers. In some states, creditors may collect up to 100% of wages while this rate is fixed at 20% in others. Moreover, some states have extensive regulations to protect debtors from abusive creditors.[36]

[34]My findings are consistent with related work inspecting the dynamics of income risk in the US over a longer time horizon. Using information on individual earnings in the CPS linked to Social Security Administration earnings records, Braxton, Herkenhoff, Rothbaum, and Schmidt (2021) do not find evidence that geography explains differences in the evolution of earnings dynamics.

[35]See, for instance, Dick and Lehnert (2010) or Gropp, Scholz, and White (1997).

[36]Differences in these policies may have ambiguous general equilibrium effects regarding the supply and cost of consumer credit. However, my sole objective is to study if these state policy variables co-move with state tax and transfer progressivity.

I collect indicators summarizing the intensity of each state's debtor protection legislation from Dawsey, Hynes, and Ausubel (2013). Columns (4) and (5) of table 11 show the results of regressing the measure of state tax and transfer progressivity on their binary indicators summarizing states' wage garnishment and debtor policy stringency. None of them is systematically related to state tax and transfer progressivity. Hence, cross-state differences in liquidity and borrowing constraints cannot help to explain systematic cross-state MPC heterogeneity.

	State Progressivity					
	(1)	(2)	(3)	(4)	(5)	(6)
Persistent Risk	-0.188					-0.164
	(0.358)					(0.423)
Transitory Risk		0.055				-0.001
		(0.210)				(0.242)
State Minimum Wage			0.001			0.002
			(0.003)			(0.004)
Wage Garnishment Stringency				0.691		0.720
				(0.537)		(0.586)
Debtor Protection					0.258	0.084
					(0.493)	(0.530)
Census Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
N	50	50	50	50	50	50
R^2	0.075	0.071	0.072	0.103	0.075	0.114

Table 11: *Correlates of state tax and transfer progressivity. Column (6) controls for all state characteristics simultaneously. All regressions include census region fixed effects. Washington DC excluded to due missing information on credit regulations. Census region fixed effects absorb additional cross state variation (as I cannot control for state fixed effects).*

8 Conclusion

This paper studies regional differences in the household consumption response to fiscal stimulus payments. I find sizable differences in average household MPCs across state groups. Given recent empirical findings on the impact of preference heterogeneity on MPCs and evidence on the relevance of regional factors in forming risk preferences, I estimate a measure of risk aversion for households in high and low MPC states. I find an inverse relationship between risk aversion and MPCs; households in states where MPCs are lower are more risk averse. My quantitative investigation in a heterogeneous-agent model with incomplete markets confirms that state heterogeneity in risk aversion has a sizable effect on cross-state MPC differences; for the values of risk aversion I estimated, the model yields predictions explaining a substantial share of cross-state variation in consumption responses to stimulus payments.

The model predictions regarding cross-state differences in portfolio liquidity hold up in the data – households in more risk averse states are less likely to be liquidity constrained, i.e. to exhibit hand-to-mouth consumption behavior out of transitory income shocks. The model also shows that risk aversion determines MPCs through a non-financial mechanism; it regulates the curvature of the consumption function. Thus, even after controlling for observable differences in liquid assets, risk aversion can explain residual heterogeneity in MPCs.

To provide additional verification for regional risk aversion differences, I derive a mapping from risk aversion to measurable state level outcomes; I show that more risk averse individuals prefer more social insurance. Using a novel measure on state tax and transfer progressivity, I demonstrate that states in which I estimated more risk aversion have more progressive tax and transfer systems.

In addition to risk aversion and tax progressivity, I also consider other state characteristics which might explain cross-state variation in MPCs (wage and credit market regulations, persistent and transitory components of earnings risk). However, none of them differs systematically between high and low MPC states. Hence, they are not suitable candidates to explain additional cross-state MPC heterogeneity.

In summary, this paper's key finding is that differences in household risk aversion are an important determinant of consumption responses to fiscal stimulus programs. They can explain sizable shares of differences in MPCs. Moreover, they manifest themselves in regional consumption response differences as well as in heterogeneity of state tax and transfer programs. Finally, this paper also highlights that even conditional on identical amounts of precautionary savings, more risk averse households are more prone to spend larger fractions of transitory income shocks.

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Appendices

A The Consumption Response to Cash Checks

A.1 Baseline results with merged state identifiers

In order to investigate regional differences in the MPCs out of stimulus checks, I obtain the CE datasets used in the analysis of Johnson, Parker, and Souleles (2006) and Parker, Souleles, Johnson, and McClelland (2013). These datasets do not contain information on the residence of households but they contain the household identification variable NEWID which I use to link households in this dataset to the CEX Public Use Microdata (PUMD) files. These contain a variable on survey respondents' state of residence. The number of observations by state in the datasets for both years is shown in figure 1.

However, in the PUMD files, about 14% of the observations lack the state identifier for reasons of confidentiality.[37] As a result, the number of observations in my estimation datasets is different from the benchmark datasets.

Tables 12 and 13 show that removing these observations does not lead to qualitatively different results compared to the findings presented in the reference papers. For 2001, two of the three MPC estimates only differ on the third digit, while I find a point estimate of 0.252 (relative to 0.239). However, as the standard errors are uniformly larger, so the significance level of the coefficient estimates is lower.

	Food	Strictly nondurable goods	Nondurable goods
	(1)	(2)	(3)
Rebate	0.106*	0.252*	0.379**
	(0.063)	(0.129)	(0.151)
Age	0.606**	0.577	1.476**
	(0.306)	(0.541)	(0.661)
Change in adults	167.345***	398.844***	518.913***
	(57.629)	(96.625)	(108.747)
Change in children	66.359	126.863	205.665**
	(51.053)	(89.113)	(102.145)
Month Fixed Effects	Yes	Yes	Yes
Estimator	OLS	OLS	OLS
N	13,346	13,346	13,346
R^2	0.006	0.007	0.008

Table 12: *Replicating Panel A, table 2 of Johnson, Parker, and Souleles (2006) after merging the state identifier.*

Comparing the estimation results presented in 13, to those reported by Parker, Souleles, Johnson, and McClelland (2013) shows that, for this year, the discrepancies are larger. For example,

[37] See here for details: https://www.bls.gov/cex/pumd_disclosure.htm#Geographic

the MPC estimate for food is an order of magnitude smaller (but insignificant in both sets of results). The MPC estimates for strictly nondurables and nondurables are quite similar (0.066 versus 0.079 and 0.114 and 0.121). However, as the standard errors are slightly larger than those reported by Parker, Souleles, Johnson, and McClelland (2013), only the nondurable MPC is significant in my dataset.

	Food	Strictly nondurable goods	Nondurable goods
	(1)	(2)	(3)
ESP	0.006	0.066	0.114*
	(0.030)	(0.050)	(0.060)
Age	0.933**	-0.008	1.374
	(0.389)	(0.705)	(0.888)
Change in adults	221.672***	473.435***	575.845***
	(61.966)	(120.304)	(133.683)
Change in children	101.849**	89.413	128.788
	(51.588)	(101.618)	(118.924)
Month Fixed Effects	Yes	Yes	Yes
Estimator	OLS	OLS	OLS
N	15,019	15,019	15,019
R^2	0.006	0.017	0.013

Table 13: *Replicating Panel A, table 2 of Parker, Souleles, Johnson, and McClelland (2013) after merging the state identifier.*

	Food	Strictly nondurable	Nondurable
	(1)	(2)	(3)
ESP $\times$ High MPC State = 0	-0.010	-0.046	-0.024
	(0.065)	(0.103)	(0.115)
ESP $\times$ High MPC State = 1	0.003	0.124	0.171
	(0.076)	(0.121)	(0.139)
Age	1.219**	0.380	1.725*
	(0.497)	(0.860)	(1.047)
Change adults	195.160***	343.374***	493.675***
	(68.487)	(119.819)	(135.255)
Change children	135.226*	99.787	132.672
	(71.104)	(142.541)	(158.754)
Month Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
Estimator	OLS	OLS	OLS
N	7,620	7,620	7,620
R^2	0.011	0.025	0.019

Table 14: *Comparing household MPCs in the ten highest and lowest MPC state groups in 2008.*

	Interacted State-Month Fixed Effects			State Month Slopes and State Fixed Effects		
	Food	S. nondurable	Nondurable	Food	S. nondurable	Nondurable
	(1)	(2)	(3)	(4)	(5)	(6)
Rebate × High MPC State = 0	-0.045	-0.134	0.043	-0.017	-0.049	0.086
	(0.099)	(0.194)	(0.225)	(0.102)	(0.199)	(0.230)
Rebate × High MPC State = 1	0.247*	0.613***	0.561**	0.198	0.478*	0.493*
	(0.127)	(0.236)	(0.280)	(0.132)	(0.245)	(0.291)
Age	0.619*	0.737	1.455*	0.572	0.684	1.376
	(0.376)	(0.664)	(0.881)	(0.377)	(0.661)	(0.881)
Change adults	92.520*	230.593**	305.215***	94.116*	230.312**	302.842***
	(48.591)	(106.078)	(117.492)	(48.814)	(105.989)	(117.136)
Change children	38.563	80.944	152.376	40.094	76.649	145.075
	(68.692)	(113.578)	(126.279)	(69.172)	(114.415)	(126.645)
State-Month Interactions	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects				Yes	Yes	Yes
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
N	6,475	6,475	6,475	6,475	6,475	6,475
R^2	0.004	0.006	0.006	0.007	0.009	0.009

Table 15: *Comparing household MPCs in the ten highest and lowest MPC states using interacted state-month fixed effects and state specific month slopes.*

A.2 Robustness: MPC Differences between the highest and lowest MPC state groups

Columns (1) to (3) of table 15 report results of estimating equation (3) using state-month interacted fixed effects which absorb MPC differences due to time and state varying sources of variation. This estimation captures state and time specific effects on MPCs such as distinct exposures to the 2001 recession or differences in state policies aiming to support household incomes. Columns (4) to (6) show the results of estimating equation (3) using state specific month slopes in addition to state fixed-effects. This specification considers explicitly that, conditional on the same month, states could have different average household MPCs due to differences in the increase of the unemployment rate or other factors explaining household consumption choices.

In all of these estimations, the differences in average household MPCs between states with the smallest and largest average MPCs remain large in magnitude. For the interacted state and month fixed effects, their statistical significance also remains large. For the state month slopes and the state fixed effects, the magnitude of the estimated differences remains large but their statistical significance diminishes for the case of expenditures on food and falls to the 10% level for strictly nondurables and non-durables.

A.3 Results for 2008

Compared to the results of 2001, the relationship between state tax and transfer progressivity is much smaller for this stimulus episode. For strictly non-durables and non durables, the MPC estimates in the group with the most regressive states tend to be larger than the sample average estimate. However, they are, as all MPC estimates for the groups with more progressive states, never statistically different from zero. In fact, the only MPC estimates of this year which are statistically different from zero at the 95% level of confidence are the non durables consumption responses in the more regressive states. Yet, as indicated by the right panel of this figure, mean MPC estimates never differ between groups.

What explains the discrepancies between the stimulus check consumption response in 2001 and 2008? The first answer is that dropping households without identified state of residence in my datasets generally results in lower significance of mean MPCs estimates. In fact, as reported in table 13 in the appendix, the only significant MPC estimate in 2008 is for spending on non durable goods. The second answer is that all MPC estimates for the 2008 episode are substantially smaller than for the 2001 episode, even in the full sample. Differences in the design of the stimulus programs play a important role in this dimension. As pointed out by Parker, Souleles, Johnson, and McClelland (2013), ”larger payments can skew the composition of spending towards durables, which is consistent with our findings given that the 2008 stimulus rebate payments were on average about twice the size of the 2001 rebates” (page 2532).

To assess how dropping observations without identified state of residence affects the sample estimates, I repeat the baseline estimation of Johnson, Parker, and Souleles (2006), as specified in equation (1). The results presented in table 12 in appendix A.1 show that dropping households without identified state of residence does not alter the literature baseline results; the MPC estimates are identical, for food and nondurable goods up to the third digit. However, the standard errors are slightly larger than reported by Johnson, Parker, and Souleles (2006).

(a) *Group Mean Estimates 2008* (b) *Group Difference Estimates 2008*

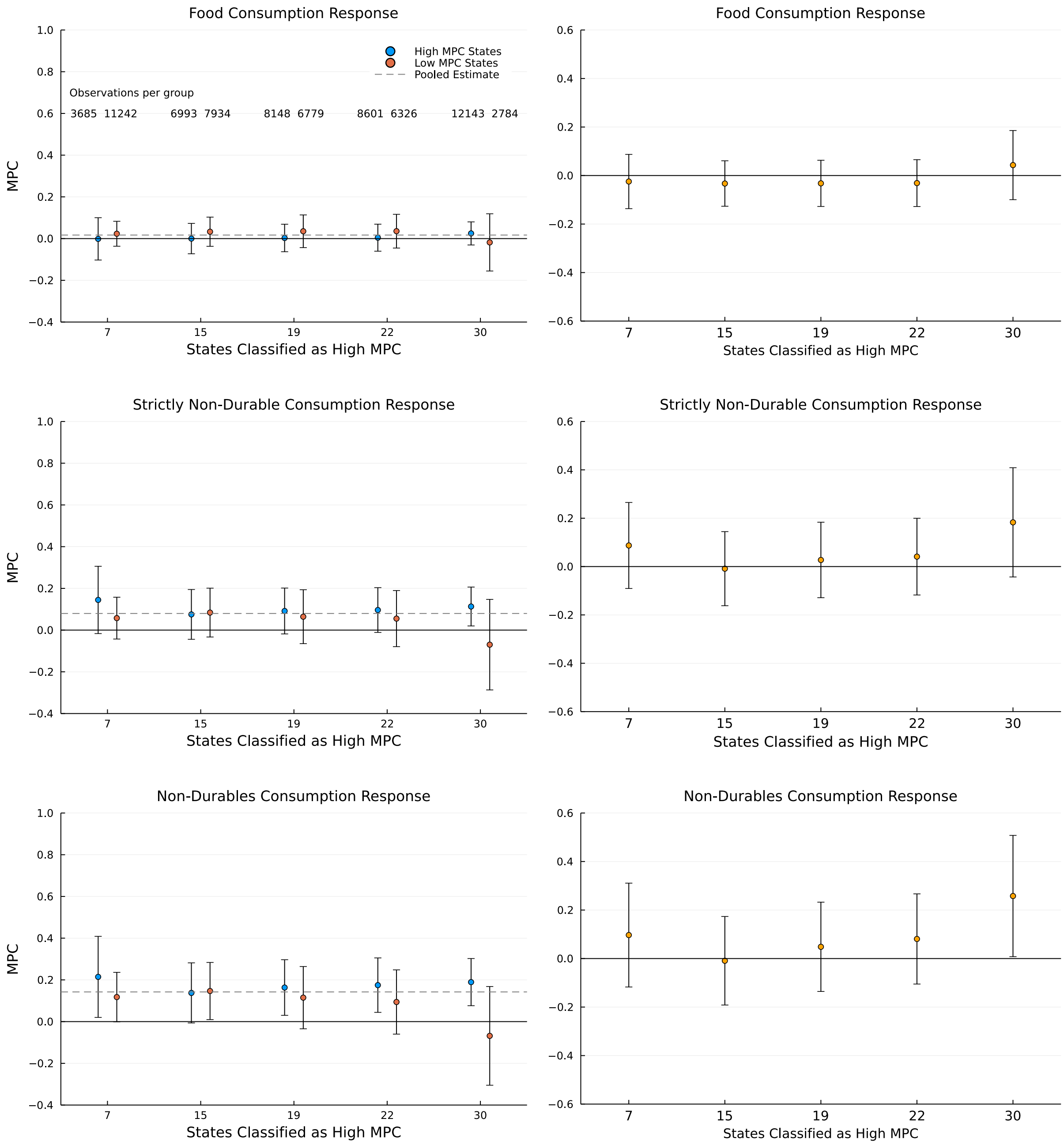

Figure 8: *Group mean and group difference estimates with 95% confidence intervals of average MPCs in 2008 for different consumption categories. States sorted into different groups according to state average MPCs. Total number of states identified in CE sample: 39*

B Risk Aversion Estimates across States

B.1 Additional Results of the GMM Estimation

For both instruments, the F-statistics of a first stage regression are 22.1 and 24.8, respectively. Hence, using Stock and Watson's rule of thumb, the coefficient estimate can be expected to

	Instrument Set 1	Instrument Set 2	
	$\hat{\gamma}$	$\hat{\gamma}$	*J Test*
All observations	2.21** (1.02)	2.30** (0.97)	0.200
10 lowest MPC states	**2.35**** (1.12)	**2.41*** (1.27)	0.147
10 highest MPC states	**1.97**** (1.00)	**1.94**** (0.82)	0.164
p-value Wald Test: $\gamma_H = \gamma_L$	*0.044*	*0.042*	
Only asset holders	2.32* (1.26)	2.34* (1.22)	0.187
10 lowest MPC states	2.41* (1.24)	2.50* (1.40)	0.157
10 highest MPC states	1.88 (1.33)	1.94* (1.11)	0.173
p-value Wald Test: $\gamma_H = \gamma_L$	*0.083*	*0.091*	

Table 16: ** 10%, ** 5% level of significance (standard errors). Instrument Set 1: lagged log real Treasury bill rate. Instrument Set 2: lagged log real Treasury bill rate, lagged log real NYSE return. First-stage F-statistic: 22.1 and 28.4*

be unbiased and valid statistical inference can be drawn. Moreover, the p-values of J tests for overidentifying restrictions are all large enough so I can reject the test's null hypothesis (all instruments are zero simultaneously) at all convential values of statistical significance.

B.2 Alternative Specification

I also estimate risk aversion using a modified version of the approach presented in Vissing-Jørgensen (2002). Thus, analogously to the analysis of cross-state differences in average MPCs, I estimate

$$\log(C_{i,t+1}) - \log(C_{i,t}) = \alpha \log(1 + r_t)d_s + \delta' Y_{s,t} + \phi' X_{i,t} + u_{i,t+1} + v_s \tag{92}$$

where, as before, d_s is an indicator which I use to sort households into high and low MPC state groups. r_t is the real federal funds rate at t so that $1/\alpha = \gamma$ is the average coefficient of risk aversion of households in the two different groups. $Y_{s,t}$ is a vector of state controls (income growth as measured by the state employment rate as well as a measure for state specific earnings risk).[38] I include these controls to capture state specific precautionary saving and smoothing motives. $X_{i,t}$ is a set of household controls. An individual error term and time (quarter) and state fixed effects are included as before.

The panels of figure 9 present my results. As for the MPC estimates presented earlier, the left (a) panels show mean estimates of my parameter of interest, $\hat{\gamma}$, for households in state groups with different average MPCs. Again, the estimate on the left compares its mean estimate of households in the ten states with the highest MPCs to its mean estimate of households in the

[38]See appendix F for a description of this measure.

30 staets with lower MPCs. Moving to the right changes this split in favor of adding more states to the low MPC group (and removing them from the high MPC group). The top panel shows the risk aversion estimates when $C_{i,t+1}$ and $C_{i,t}$ refer to food consumption. The middle and bottom panel show them for strictly nondurables and nondurables. The right (b) panels of figure 9 show group difference estimates of $\hat{\gamma}$, referring to the same category of consumption as the adjacent plot on the left panel.

(a) *Group Mean Estimates 2001* (b) *Group Difference Estimates 2001*

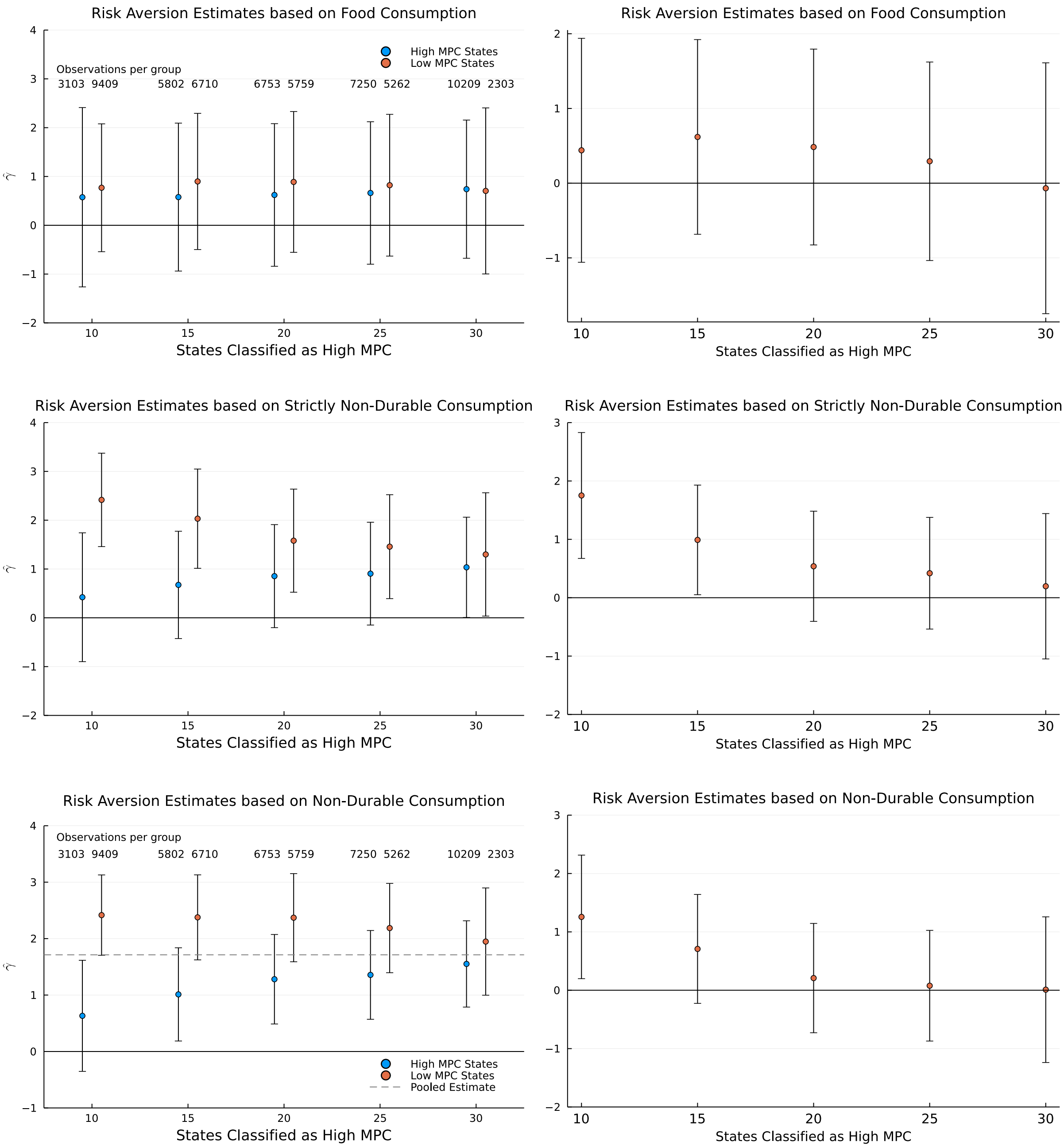

Figure 9: *Mean and group difference estimates of average risk aversion in 2001. Based on estimating Euler Equations for different consumption expenditure categories. Error bars show 95% confidence intervals. Households sorted into different groups according to average MPC estimates. Total number of states identified in the CE sample: 40*

When I use food consumption to measure changes in log consumption in equation (92), I find estimates of the coefficient of relative risk aversion between 0.6 and 0.9. However, none of the estimates are statistically different from zero. Moreover, they do not differ statistically between households in high and low MPC states. For strictly non-durables and non-durables, the risk aversion coefficient estimates are always larger for households in the low MPC states and in the range of 1.2 to 2.6. In comparison, for households in the states with the largest average MPCs, they are either not statistically different from zero or estimated at values below 1.6.

Taking stock, the evidence on cross-state differences in risk aversion confirms the empirical relationship I found in the baseline (GMM) estimation; households in states with higher average MPCs tend to be less risk averse than those in low MPC states states. The differences in the estimated coefficients of risk aversion are sizable; depending on the consumption category used when estimating equation (92), they are between 1.2 and 2 in low MPC states and indistinguishable from zero or no larger than 1.5 in high MPC states.

C Constructing Portfolio Measures from Tax Returns

For the United States, the primary data source for household portfolio items is the Federal Reserve's Survey of Consumer Finances (SCF). However, even though the survey files contain information on respondents' state of residence[39], its public release data files do not include this geographic variable to protect the anonymity of participants. Some tabulations for the Census regions (Northeast, Midwest, South, West) are publicly available. However, as they aggregate respondents from a large number of states, they are too granular to draw conclusions about portfolio differences between states. Moreover, they include only a few asset and liability variables which do not allow to construct indicators measuring differences in liquidity structures of household savings.

C.1 Average Liquid Assets in different State Groups

Given this limitation, I construct a measure for state liquid assets which is based on state level data from the Internal Revenue Service's (IRS) Statistics of Income Division (SOI). Specifically, I work with different years of the "Historic Table 2" collection published by SOI's tax statistics.[40] These tables provide information on aggregate tax returns by states for different groups of Adjusted Gross Income (AGI). For example, for different AGI groups, they report total salary and wage income as well as the total number of returns. Non-labor incomes related to liquid assets is "Taxable Interest Income" which captures holdings of specific amounts of liquid assets.

I follow Saez and Zucman (2016) and capitalize these income flows to stocks of liquid assets using a hypothetical rate of return. It has been pointed out, for example by Smith, Zidar, and Zwick (2020), that this capitalization approach leads to biased estimates due to systematic re-

[39] Variable X30045: "State-County (FIPS) code".

[40] Available here: https://www.irs.gov/statistics/soi-tax-stats-historic-table-2

turn variability. As high asset individuals tend to earn higher interests in their investments, assuming a common rate of return overestimates the capitalized asset holdings at the top end of the distribution. However, my objective is not to compare liquid assets of individuals with different levels of wealth but to measure systematic differences in liquid wealth of households with similar incomes in different states. Thus, this critique applies to my approach only insofar as there is return variability across states.

Capitalizing interest income Let states be indexed by s, years by t and adjusted gross income (AGI) groups by k. Then, I can use the SOI data to impute the nominal values $a_{s,k,t}$ of the liquid assets generating the reported incomes as

$$a_{s,k,t} = \frac{\frac{\text{Amount: Taxable Interest}_{s,k,t}}{\text{Number of Returns: Taxable Interest}_{s,k,t}}}{i} \tag{93}$$

$$= \frac{\text{Average Interest Income}_{s,k,t}}{\text{Short-term Interest Rate}} \tag{94}$$

where i denotes a common rate of return. As a measure for this uniform short-term interest rate, I use the annualized Effective Federal Funds Rate of year t.

Constructing liquid wealth/income measures Using the stocks of liquid assets for different states, AGI groups and years, $a_{s,k,t}$, I generate liquid wealth income ratios by dividing the stocks for a given state and year with the corresponding AGI incomes of each group k. As my interest is to generate state averages, I compute weights for each AGI group.[41] I compute these weights using the share of each AGI group in the total tax returns reported in state s in year t.

C.2 Constructing Stock Market Participation Rates

The tax return files provided by the IRS SOI also include information on the receipt of (ordinary) dividend income. Analogous to interest income, I use this information to compute the share of tax filers who reported dividend income within each AGI group for each state and year. Figure 10 illustrates these stock market participation rates in the ten states with the highest and lowest estimated intensities of risk aversion. As the figure shows, stock market participation is larger in states for which I estimated low risk aversion intensities. This finding provides evidence in favor of systematic geographic risk aversion differences in the US.

[41]For 2001, these groups were: \$0 to \$10,000, \$10,000 to \$20,000, \$20,000 to \$30,000, \$30,000 to \$50,000, \$50,000 to \$75,000, \$75,000 to \$100,000, \$100,000 to \$150,000, \$150,000 to \$200,000, \$500,000 to \$1,000,000, more than \$1,000,000.

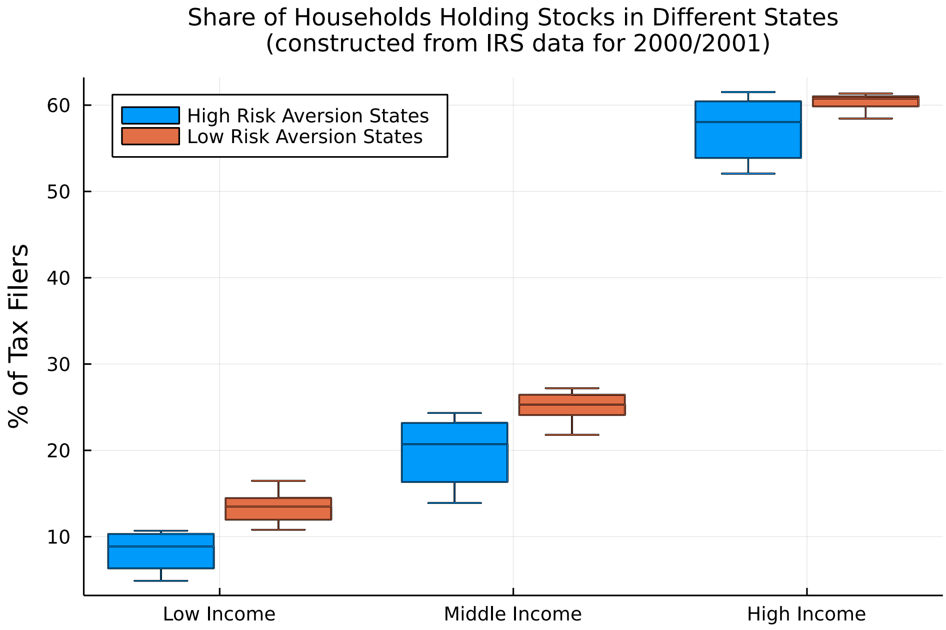

Figure 10: *Average shares of stock market participants in different states; low income: \$0 to \$20,000 AGI, middle income: \$20,000 to \$50,000 AGI, high: \$50,000 to \$200,000 AGI*

D Risk Aversion and Tax Progressivity

D.1 Computing Equilibrium Allocations in the No Tax Economy

The social planner problem for an island with given α is

$$\max_{c,h} \int_E u(c,h)\, d\Phi_{v_\varepsilon}(\varepsilon) \tag{95}$$

subject to the resource constraint

$$\int_E wh - c\, d\Phi_{v_\varepsilon}(\varepsilon) = 0 \tag{96}$$

The associated first order conditions are

$$c = \mu^{-\frac{1}{\gamma}} \tag{97}$$

$$h = c^{-\frac{\gamma}{\sigma}} \exp\left(\frac{\alpha+\varepsilon}{\sigma}\right) \tag{98}$$

$$= \mu^{\frac{1}{\sigma}} \exp\left(\frac{\alpha+\varepsilon}{\sigma}\right) \tag{99}$$

Substitute them into the resource constraint to compute the value of the multiplier μ

$$\int_E wh - c\, d\Phi_{v_\varepsilon}(\varepsilon) = 0 \tag{100}$$

$$\int_E w\mu^{\frac{1}{\sigma}} \exp\left(\frac{\alpha+\varepsilon}{\sigma}\right) - \mu^{-\frac{1}{\gamma}}\, d\Phi_{v_\varepsilon}(\varepsilon) = 0 \tag{101}$$

$$\int_E w^{1+\frac{1}{\sigma}} \mu^{\frac{1}{\sigma}} - \mu^{-\frac{1}{\gamma}} \, d\Phi_{v_\varepsilon}(\varepsilon) = 0 \tag{102}$$

$$\mu^{\frac{1}{\sigma}} \int_E w^{1+\frac{1}{\sigma}} \, d\Phi_{v_\varepsilon}(\varepsilon) = \mu^{-\frac{1}{\gamma}} \tag{103}$$

$$\exp\left(\frac{1+\sigma}{\sigma}\left(\alpha + \frac{1}{\sigma}\frac{v_\varepsilon}{2}\right)\right) = \mu^{-\left(\frac{1}{\sigma}+\frac{1}{\gamma}\right)} \tag{104}$$

$$-\left(\frac{1+\sigma}{\sigma}\left(\alpha + \frac{1}{\sigma}\frac{v_\varepsilon}{2}\right)\right) = \left(\frac{1}{\sigma} + \frac{1}{\gamma}\right) \log \mu \tag{105}$$

$$\exp\left(-\gamma\left(\frac{1+\sigma}{\sigma+\gamma}\right)\left(\alpha + \frac{1}{\sigma}\frac{v_\varepsilon}{2}\right)\right) = \mu \tag{106}$$

Plugging μ into the first order conditions (97) and (99) results in the equilibrium allocations shown in equations (24) and (25).

D.2 Computing the Average Tax Rate

For a given τ, there is a unique value λ^* such at that the tax and transfer system respects the aggregate resource constraint, i.e. equalizes aggregate consumption and production. As a function of all model primitives (including τ) it can be computed as follows; start from the aggregate resource constraint and solve for λ

$$C = Y \tag{107}$$

$$\int_A \int_E wh \, d\Phi_{v_\varepsilon}(\varepsilon) \, d\Phi_{v_\alpha}(\alpha) = \int_A \int_E \lambda (wh)^{1-\tau} \, d\Phi_{v_\varepsilon}(\varepsilon) \, d\Phi_{v_\alpha}(\alpha) \tag{108}$$

$$\lambda = \frac{\int_A \int_E wh \, d\Phi_{v_\varepsilon}(\varepsilon) \, d\Phi_{v_\alpha}(\alpha)}{\int_A \int_E (wh)^{1-\tau} \, d\Phi_{v_\varepsilon}(\varepsilon) \, d\Phi_{v_\alpha}(\alpha)} \tag{109}$$

Note that the multiplier μ is a function of α so it needs to be accounted for when computing the integral over α. For the ease of exposition, compute first the numerator and then the denominator.

Begin with the numerator

$$\int_A \int_E wh \, d\Phi_{v_\varepsilon}(\varepsilon) \, d\Phi_{v_\alpha}(\alpha) = \int_A \int_E \exp(\varepsilon + \alpha) h \, d\Phi_{v_\varepsilon}(\varepsilon) \, d\Phi_{v_\alpha}(\alpha) \tag{110}$$

Use the expression for h from equation (49) and define $\kappa_{v_\varepsilon} = \frac{1+\hat{\sigma}}{\gamma+\hat{\sigma}}\left(1 - \tau(1+\hat{\sigma})\right)\frac{\gamma}{\hat{\sigma}^2}\frac{v_\varepsilon}{2}$ so that

$$h = \exp\left(\left(\frac{1-\gamma}{\gamma+\hat{\sigma}}\right)\alpha + \frac{1}{\hat{\sigma}}\varepsilon - \kappa_{v_\varepsilon} - \kappa_h\right) \tag{111}$$

Substitute this term into the double integral to finish rewriting the numerator

$$\int_A \int_E \exp(\varepsilon + \alpha) \exp\left(\left(\frac{1-\gamma}{\gamma+\hat{\sigma}}\right)\alpha + \frac{1}{\hat{\sigma}}\varepsilon - \kappa_{v_\varepsilon} - \kappa_h\right) d\Phi_{v_\varepsilon}(\varepsilon) \, d\Phi_{v_\alpha}(\alpha) \tag{112}$$

$$= \exp\big(-\kappa_{v_\varepsilon} - \kappa_h\big) \int_A \int_E \exp\left(\varepsilon\left(\frac{1+\hat{\sigma}}{\hat{\sigma}}\right)\right) \exp\left(\alpha\left(\frac{1+\hat{\sigma}}{\gamma+\hat{\sigma}}\right)\right) d\Phi_{v_\varepsilon}(\varepsilon)\, d\Phi_{v_\alpha}(\alpha) \tag{113}$$

$$= \exp\big(-\kappa_{v_\varepsilon} - \kappa_h\big) \exp\left(\frac{1+\hat{\sigma}}{\hat{\sigma}^2}\frac{v_\varepsilon}{2}\right) \exp\left(\frac{(1+\hat{\sigma})(1-\gamma)}{(\gamma+\hat{\sigma})^2}\frac{v_\alpha}{2}\right) \tag{114}$$

Continue with the denominator

$$\int_A \int_E (wh)^{1-\tau}\, d\Phi_{v_\varepsilon}(\varepsilon)\, d\Phi_{v_\alpha}(\alpha) \tag{115}$$

$$= \int_A \int_E w^{1-\tau} h^{1-\tau}\, d\Phi_{v_\varepsilon}(\varepsilon)\, d\Phi_{v_\alpha}(\alpha) \tag{116}$$

$$= \int_A \int_E \Big(\exp\big(\alpha(1-\tau)\big) \exp\big(\varepsilon(1-\tau)\big)\Big) h^{1-\tau}\, d\Phi_{v_\varepsilon}(\varepsilon)\, d\Phi_{v_\alpha}(\alpha) \tag{117}$$

$$\begin{aligned} &= \exp\Big((\tau-1)\big(\kappa_{v_\varepsilon} + \kappa_h\big)\Big) \int_A \int_E \exp\big(\alpha(1-\tau)\big) \exp\big(\varepsilon(1-\tau)\big) \\ &\qquad \exp\left(\frac{(1-\gamma)(1-\tau)}{\gamma+\hat{\sigma}}\alpha\right) \exp\left(\frac{(1-\tau)}{\hat{\sigma}}\varepsilon\right) d\Phi_{v_\varepsilon}(\varepsilon)\, d\Phi_{v_\alpha}(\alpha) \end{aligned} \tag{118}$$

$$\begin{aligned} &= \exp\Big((\tau-1)\big(\kappa_{v_\varepsilon} + \kappa_h\big)\Big) \\ &\qquad \int_A \int_E \exp\big(\alpha\frac{(1-\tau)(1+\hat{\sigma})}{\gamma+\hat{\sigma}}\big) \exp\big(\varepsilon\frac{(1-\tau)(1+\hat{\sigma})}{\hat{\sigma}}\big)\, d\Phi_{v_\varepsilon}(\varepsilon)\, d\Phi_{v_\alpha}(\alpha) \end{aligned} \tag{119}$$

$$\begin{aligned} &= \exp\Big((\tau-1)\big(\kappa_{v_\varepsilon} + \kappa_h\big)\Big) \\ &\qquad \exp\left(\frac{(1-\tau)(1+\hat{\sigma})}{\hat{\sigma}^2}\big(1-\tau(1+\hat{\sigma})\big)\frac{v_\varepsilon}{2}\right) \\ &\qquad\qquad \exp\left(\frac{(1-\tau)(1+\hat{\sigma})}{(\gamma+\hat{\sigma})^2}\big(1-\gamma-\tau(1+\hat{\sigma})\big)\frac{v_\alpha}{2}\right) \end{aligned} \tag{120}$$

Begin with collecting terms in the division shown in the right hand side of equation (109). Consider κ_{v_ε} and κ_h first

$$\lambda = \exp\big(-\tau(\kappa_{v_\varepsilon} + \kappa_h)\big)\dots \tag{121}$$

$$\lambda \exp(\tau\kappa_h) = \exp\big(-\tau\kappa_{v_\varepsilon}\big)\dots \tag{122}$$

Add the numerator and denominator $\frac{v_\varepsilon}{2}$ terms:

$$\lambda \exp(\tau\kappa_h) = \exp\big(-\tau\kappa_{v_\varepsilon}\big) \exp\left(\frac{1+\hat{\sigma}}{\hat{\sigma}^2}\frac{v_\varepsilon}{2}\right) \exp\left(-\frac{(1-\tau)(1+\hat{\sigma})}{\hat{\sigma}^2}\big(1-\tau(1+\hat{\sigma})\big)\frac{v_\varepsilon}{2}\right)\dots \tag{123}$$

$$\begin{aligned} &= \exp\left(-\tau\left(\frac{1+\hat{\sigma}}{\gamma+\hat{\sigma}}\big(1-\tau(1+\hat{\sigma})\big)\frac{\gamma}{\hat{\sigma}^2}\frac{v_\varepsilon}{2}\right)\right) \exp\left(\frac{1+\hat{\sigma}}{\hat{\sigma}^2}\frac{v_\varepsilon}{2}\right) \\ &\qquad \exp\left(-\frac{(1-\tau)(1+\hat{\sigma})}{\hat{\sigma}^2}\big(1-\tau(1+\hat{\sigma})\big)\frac{v_\varepsilon}{2}\right)\dots \end{aligned} \tag{124}$$

$$= \exp\left(-\tau\Big(\frac{\gamma}{\gamma+\hat{\sigma}}\frac{1+\hat{\sigma}}{\hat{\sigma}^2}(1-\tau(1+\hat{\sigma}))\frac{v_\varepsilon}{2}\Big)\right)\exp\left(\frac{1+\hat{\sigma}}{\hat{\sigma}^2}\frac{v_\varepsilon}{2}\right)$$
$$\exp\left((\tau-1)\Big(\frac{(1+\hat{\sigma})}{\hat{\sigma}^2}(1-\tau(1+\hat{\sigma}))\frac{v_\varepsilon}{2}\Big)\right)\dots \tag{125}$$

Define $\psi_\varepsilon = 1-\tau(1+\hat{\sigma})$ to simplify notation

$$\lambda\exp(\tau\kappa_h) = \exp\left(-\tau\Big(\frac{\gamma}{\gamma+\hat{\sigma}}\frac{1+\hat{\sigma}}{\hat{\sigma}^2}\psi_\varepsilon\frac{v_\varepsilon}{2}\Big)\right)\exp\left(\frac{1+\hat{\sigma}}{\hat{\sigma}^2}\frac{v_\varepsilon}{2}\right)\exp\left((\tau-1)\Big(\frac{(1+\hat{\sigma})}{\hat{\sigma}^2}\psi_\varepsilon\frac{v_\varepsilon}{2}\Big)\right)\dots \tag{126}$$

$$= \exp\left(\frac{v_\varepsilon}{2}\frac{1+\hat{\sigma}}{\hat{\sigma}^2}\Big(1+\psi_\varepsilon\Big(\tau(\frac{\hat{\sigma}}{\gamma+\hat{\sigma}})-1\Big)\Big)\right) = \exp(\chi_\varepsilon)\dots \tag{127}$$

Add the numerator and denominator $\frac{v_\alpha}{2}$ terms:

$$\lambda\exp(\tau\kappa_h) = \exp(\chi_\varepsilon)\exp\left(\frac{(1+\hat{\sigma})(1-\gamma)}{(\gamma+\hat{\sigma})^2}\frac{v_\alpha}{2}\right)\exp\left(\frac{(1-\tau)(1+\hat{\sigma})}{(\gamma+\hat{\sigma})^2}(1-\gamma-\tau(1+\hat{\sigma}))\frac{v_\alpha}{2}\right) \tag{128}$$

Let $\psi_\alpha = 1-\gamma-\tau(1+\hat{\sigma})$

$$\lambda\exp(\tau\kappa_h) = \exp(\chi_\varepsilon)\exp\left((1-\gamma)\frac{(1+\hat{\sigma})}{(\gamma+\hat{\sigma})^2}\frac{v_\alpha}{2}\right)\exp\left((1-\tau)\frac{(1+\hat{\sigma})}{(\gamma+\hat{\sigma})^2}\psi_\alpha\frac{v_\alpha}{2}\right) \tag{129}$$
$$= \exp(\chi_\varepsilon)\exp\left(\frac{v_\alpha}{2}\frac{1+\hat{\sigma}}{(\gamma+\hat{\sigma})^2}\Big(1-\gamma+(1-\tau)\psi_\alpha\Big)\right) \tag{130}$$
$$= \exp(\chi_\varepsilon)\exp(\chi_\alpha) \tag{131}$$

Substitute $\kappa_h = \frac{1}{(1-\tau)(\gamma+\hat{\sigma})}\Big(\log\Big(\lambda^{1-\gamma}(1-\tau)\Big)\Big)$ into the left hand term and flip sides

$$\exp(\chi_\varepsilon)\exp(\chi_\alpha) = \lambda\exp(\tau\kappa_h) \tag{132}$$
$$\exp(\chi_\varepsilon+\chi_\alpha) = \lambda\exp\left(\frac{\tau}{(1-\tau)(\gamma+\hat{\sigma})}\Big(\log\Big(\lambda^{1-\gamma}(1-\tau)\Big)\Big)\right) \tag{133}$$
$$= \lambda\Big(\lambda^{1-\gamma}(1-\tau)\Big)^{\frac{\tau}{(1-\tau)(\gamma+\hat{\sigma})}} \tag{134}$$
$$= \lambda^{\frac{(1-\tau)(\gamma+\hat{\sigma})+\tau(1-\gamma)}{(1-\tau)(\gamma+\hat{\sigma})}}(1-\tau)^{\frac{\tau}{(1-\tau)(\gamma+\hat{\sigma})}} \tag{135}$$
$$\exp(\chi_\varepsilon+\chi_\alpha)(1-\tau)^{-\frac{\tau}{(1-\tau)(\gamma+\hat{\sigma})}} = \lambda^{\frac{(1-\tau)(\gamma+\hat{\sigma})+\tau(1-\gamma)}{(1-\tau)(\gamma+\hat{\sigma})}} \tag{136}$$
$$\lambda^* = \exp\left((\chi_\varepsilon+\chi_\alpha)\frac{(1-\tau)(\gamma+\hat{\sigma})}{(1-\tau)(\gamma+\hat{\sigma})+\tau(1-\gamma)}\right)(1-\tau)^{-\frac{\tau}{(1-\tau)(\gamma+\hat{\sigma})+\tau(1-\gamma)}} \tag{137}$$

Thus, as illustrated by equation (137), for a given value of τ, the corresponding average tax rate

λ^*, which respects the economy's aggregate resource constraint, has a closed form solution in the primitives of the model $\gamma, \sigma, v_\alpha, v_\varepsilon$.

E Measuring State Tax and Transfer Progressivity

E.1 Separating Federal and State Taxes and Transfers

Table 17 shows all taxes and transfers considered in the estimation of Fleck, Heathcote, Storesletten, and Violante (2021). Their narrow measure includes all state and federal transfers which are typically associated with the US social safety net, i.e. TANF, SNAP, UI, DI and Survivors Insurance.[42] In their broad measure, all other transfers are also included.

	Federal		State & Local	
		% inc		*% inc*
Taxes	Income	*10.99*	Income	*3.26*
	FICA	*6.47*	Property	*2.89*
			Sales	*0.86*
			Excise + User Charges	*0.61*
Transfers	Medicaid*	*1.19*	UI	*1.12*
	Survivors Insurance	*1.13*	Medicaid*	*0.58*
	SNAP	*0.33*	Workers' Comp.	*0.15*
	SSI	*0.21*	TANF*	*0.01*
	Veteran's Benefits	*0.19*		
	DI	*0.17*		
	School Lunch	*0.16*		
	TANF*	*0.01*		

Table 17: *Classification of federal and state and local taxes and transfers. Taxes and transfers are reported as shares of pre-government income. Transfers marked with an asterisk have both federal and state components.*

Low TANF Prevalence Table 17 indicates that Temporary Assistance for Needy Families (TANF) is the smallest of all transfer programs considered in their investigation and makes up a smaller share of transfer program than reported in administrative data. The reason for this discrepancy is that FHSV select a sample which consists of households with heads older than 25 (but younger than 60) in which at least one spouse had an income equal to or larger than working part time at the minimum wage. Yet, the bulk of TANF recipients are young mothers. In fact, about one third of all recipients are younger than 25. Moreover, as TANF has

[42] For households in Alaska, Fleck, Heathcote, Storesletten, and Violante (2021) also include the Alaska Permanent Fund Dividend (APFD) which is a key driver of estimated progressivity in this state.

life-time limits, parents with children who are old enough to qualify for other programs, such as school lunch, are typically no longer eligible. Finally, many recipients do not have enough earned income to meet the income requirement. Hence, both of these selection conditions result in low TANF prevalence in the sample.

Splitting Joint Programs Two transfer programs, Temporary Assistance for Needy Families (TANF) and Medicaid, are federally mandated programs but have state options; within federal guidelines, states can choose parameters determining the eligibility and generosity of these programs. These choices lead to substantial cross-state progressivity differences of both transfer programs. Thus, it is essential to separate the receipts reported by households into federal versus state shares.

Federal funding for TANF is provided via block grants. To account for different shares in state and federal TANF funding I follow FHSV and compute the federal share f_s^{TANF} for each state s using program data from the Office of Family Assistance (OFA) website. The resulting federal shares range from 29% (Washington) to 83% (West Virgina) with a mean (median) of 59% (60%). They are illustrated in figure 11.

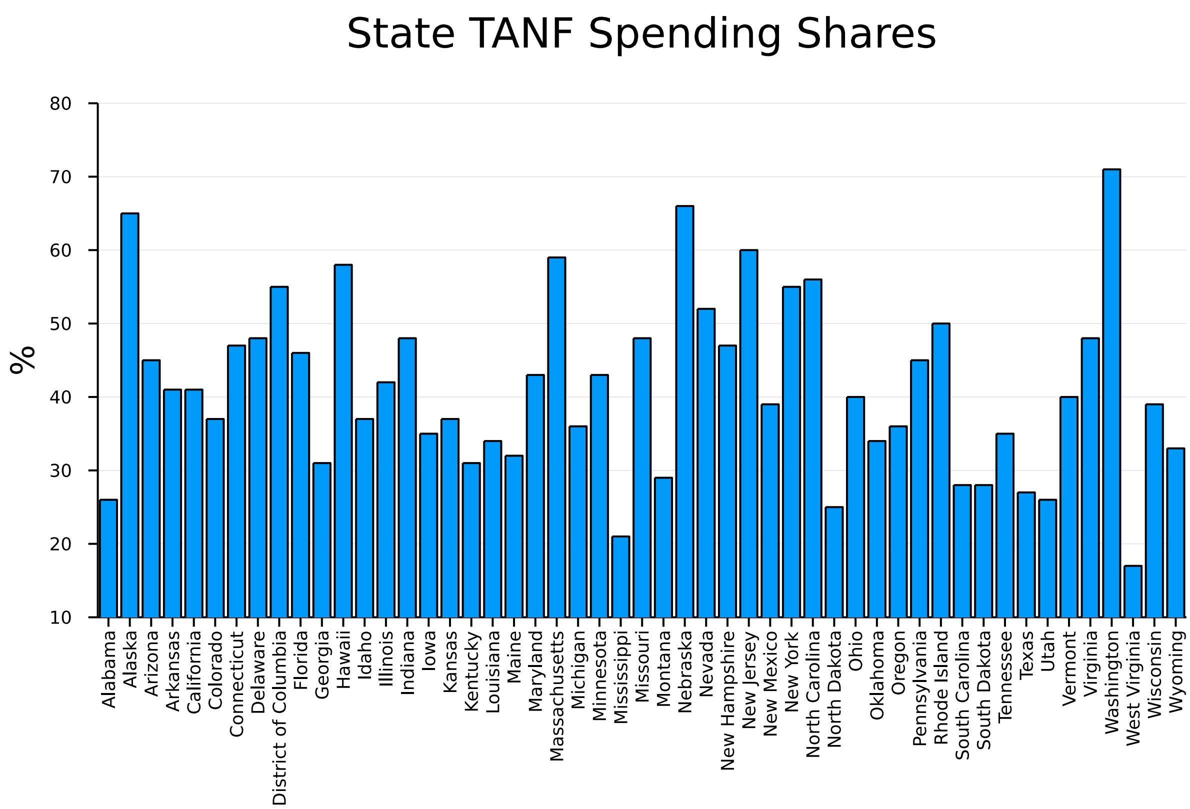

Figure 11: *Computed from Office of Family Assistance (OFA) data on federal and state assistance and non-assistance expenditures for 2010.*

I use these shares to compute state and federally funded TANF benefits as

$$\text{State TANF Benefit}_{i,t,s} = (1 - f_s^{TANF}) \times \text{TANF Benefit}_{i,t,s} \tag{138}$$

$$\text{Federal TANF Benefit}_{i,t,s} = f_s^{TANF} \times \text{TANF Benefit}_{i,t,s} \tag{139}$$

Medicaid and the Children's Health Insurance Program (CHIP) are funded from state funds and federal matching grants. The size of each state's federal grant is determined by the Federal Medical Assistance Percentage (FMAP). For each year t these rates are computed from state s income relative to national US income using the formula

$$\text{FMAP}_{s,t} = \max\left\{\frac{\text{Per capita income}^2_{s,t}}{\text{Per capita income}^2_{US,t}} \times 0.45, 0.5\right\} \tag{140}$$

Hence, states with lower relative per capita income receive more generous federal matching grants to fund their Medicaid expenditures. Figure 12 shows the cross-state FMAP variation in 2000 and 2007. As illustrated in this figure, FMAPs range from 50% in richer states to about 75% in poorer states. To split Medicaid benefits into state and federal shares, I proceed analogously as for TANF, using the FMAP rates for each state and year to compute the federal share of Medicaid spending, $f^M_{s,t}$.

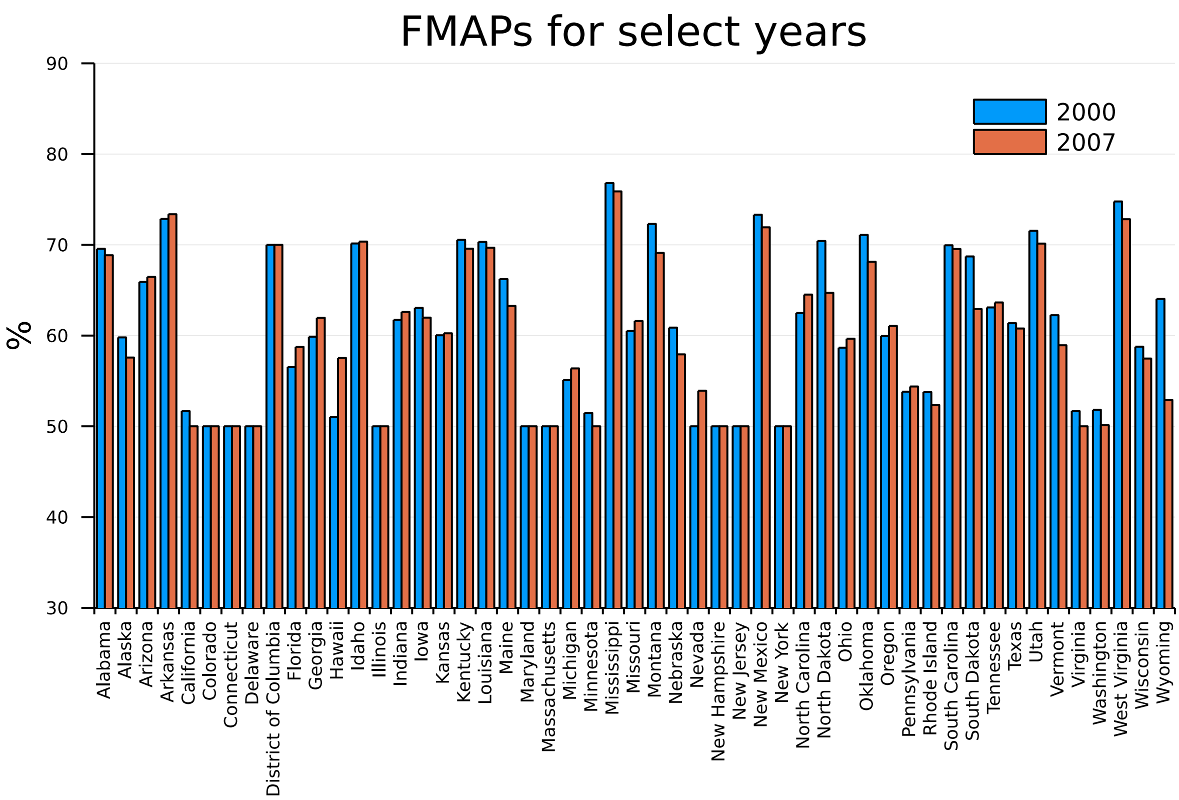

Figure 12: *Medicaid Federal Medical Assistance Percentage (FMAP) for select years*

E.2 Detailed Results of FHSV

Figure 13 shows the progressivity decomposition presented in Fleck, Heathcote, Storesletten, and Violante (2021) for the years 2010 and 2011. As the figure illustrates, income taxes and transfers are estimated to make non-negative contributions to progressivity in each state. Consumption (sales, excise) and property taxes, however, are always regressive. Thus, states which rely more heavily on these revenue instruments end up with more regressive tax and transfer systems.

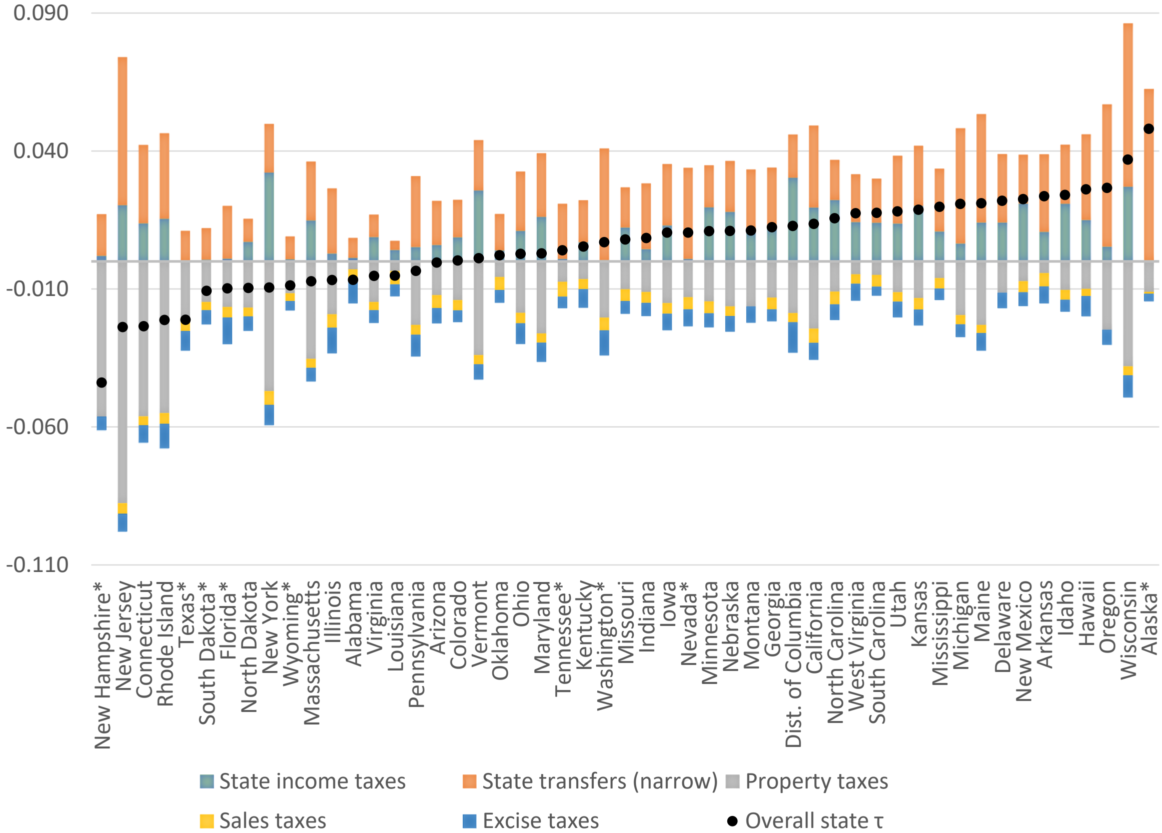

Figure 13: *Tax progressivity decomposition of Fleck, Heathcote, Storesletten, and Violante (2021) based on their narrow measure of transfers. States* without income taxes.*

E.3 Extending the State Progressivity Measure to 2001

The state progressivity measure of Fleck, Heathcote, Storesletten, and Violante (2021) refers to the years 2010 and 2011. However, as I show in this section, it's implied ranking is consistent across time. I do so by repeating the estimation for the years 2008 and 2001. I proceed analogously as Fleck, Heathcote, Storesletten, and Violante (2021), i.e. I select ASEC observations which have a household head of working age (older than 25 but younger than 60) and at least one spouse who has earnings equivalent to working part time at the minimum wage of the respective year. (For 2000 to 2002, this corresponded to an income requirement of \$5,150. For the later years, it was \$5,850, \$6,550 and \$7,250).

I select years adjacent to 2001 and 2008 (when the stimulus payments were distributed) in order to increase the number of ASEC observations by state. As shown by figure 14, this strategy provides me with no less than 3,100 observations in any state.

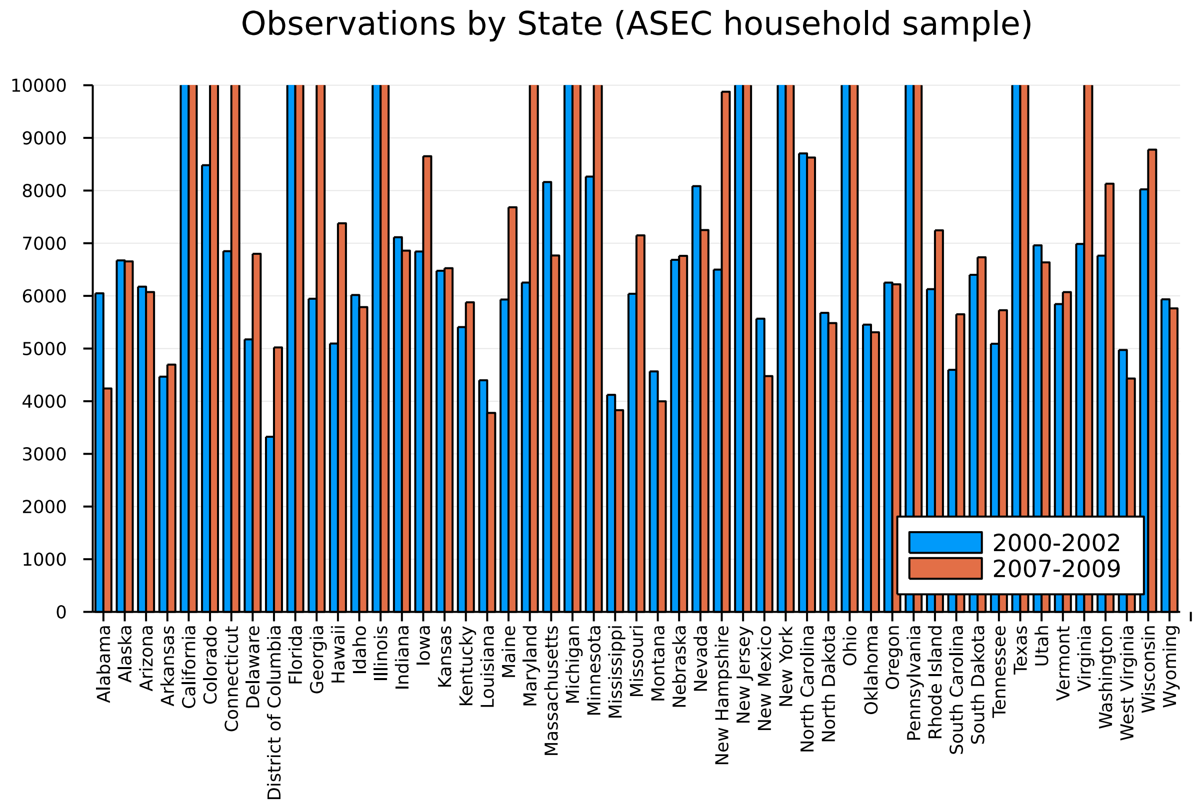

Figure 14: *Distribution of ASEC observations by state for 2000-2002 and 2007-2009.*

An essential step in the estimation of state tax and transfer progressivity is to assign federal and state income taxes and transfers to generate measures of disposable income after federal and state taxes and transfers, T_i^f and T_i^s. I follow the same procedure as Fleck, Heathcote, Storesletten, and Violante (2021) to assign transfers, i.e. I use same assignment between federal and state (see table 17). Finally, I also use the same federal-state splitting of TANF and Medicaid (see section E.1).

Income measure	Corresponding variables
$y_{i,s}$: Earnings ("Gross income")	Labor earnings + Self employment income + Private Transfers + Dividend, Rental, Interest income - Deductions + Employer Share (50%) of FICA Tax
$\tilde{y}_{i,s}$: Post-*state*-gov't	$y_{i,s}$ - state taxes + $(1 - f^M_{s,t})$ Medicaid + $(1 - f^T_{i,s})$ TANF + Unemployment Benefits + Workers Compensation
$\hat{y}_{i,s}$: Post-*state-and-federal*-gov't	$\tilde{y}_{i,s}$ - federal taxes + $f^M_{s,t}$ Medicaid + $f^T_{i,s}$ TANF + Supplementary Security Income + Veterans Pensions + Disability Insurance + Food Stamps

Table 18: *Assigning ASEC income and transfer variables*

E.4 Determining Tax Filing Status in ASEC

I use TAXSIM to impute federal and state income taxes paid by households in the ASEC dataset. Note that this tax calculator has a very detailed treatment of state income tax credits since 1977.[43]

TAXSIM requires users to determine the filing status of households. As filing status has large implications for the availability of tax credits, exemptions and deductions, I assign the status following a detailed algorithm:

1. If household has only one member, assign as single filer.
2. If more than one member:
    - If household contains married couple, assign all dependents to this couple. Assign all other non-dependents as single filers.
    - If household does not contain married couple, and no dependents, assign all as single filers.
    - If household does not contain married couple, but dependents, assign them to the household member with the highest income as household head. All others are single filers.

E.5 Limitations of the Census Bureau Tax Model

Fleck, Heathcote, Storesletten, and Violante (2021) use information on federal and state income taxes and tax credits available in the Annual Social and Economic Supplements (ASEC) in their

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

estimation. While ASEC asks respondents a range of questions on income received from different sources and transfers received, it does not survey any questions on taxes paid. Yet, the Census Bureau imputes a range of tax variables which are included in the ASEC public use files. They include federal and state income taxes as well as property taxes paid by homeowners and are provided as outputs of the Census Bureau's tax imputation model.[44] Unfortunately, as indicated by documentation on this tax imputation model, see for example O'Hara (2004), O'Hara (2006) and Webster (2011), the model has two main limitations which make it unsuitable for the purpose of estimating state tax progressivity over a longer time horizon, in particular for years prior to 2005.

Limitation 1: Missing Tax Credits Before 2005 The public ASEC files do not include state and federal tax credits prior to 2005.[45] The documentation of the Census Bureau tax model does not indicate if the reason for this is that the model does not have the capacity to impute them or if they have not been provided to the public use files. In any case, the result of this omission is that I cannot use the ASEC tax variables to construct measures for state tax progressivity prior and during the first episode of cash checks (2001). As tax credits are key provider of progressivity, omitting them would introduce systematic bias in the estimation.

Limitation 2: Erroneous Time Variation in Imputed Variables As explained in the IPUMS documentation, the ASEC variable FILESTAT reports the federal income tax filing status.[46] It provides six different tax filing status categories:

Code	**Label**
0	No data[47]
1	Joint, both less than 65
2	Joint, one less than 65 and one 65+
3	Joint, both 65+
4	Head of household
5	Single
6	Nonfiler

[44]Note that the property taxes paid are not provided by this model but result from matching ASEC observations to observations from the American Housing Survey (until 2011) and publicly available tax filer information provided by the IRS (for later years).

[45]See the availability of the IPUMS variables STATAXAC (State income tax liability, after all credits) and STATETAX (State income tax liability, before credits). Same applies to federal income taxs FEDTAXAC (Federal income tax liability, after all credits) and FEDTAX (Federal income tax liability, before credits).

[46]https://cps.ipums.org/cps-action/variables/FILESTAT#description_section

As for other ASEC tax-related variables, values of FILESTAT are imputed by the Census Bureau's tax model, i.e. they are not provided by survey respondents. The IPUMS documentation mentions that comparability of FILESTAT might have been affected by the introduction of a new Census Bureau tax model in 2004. Indeed, some users have noticed that variables imputed by the Census Bureau tax model display inconsistencies across years.[48]

To investigate these discrepancies, table 19, reproduced from Fleck (2020), displays the relative frequencies of the FILESTAT categories over a longer time period. As the table illustrates, the share of nonfilers appears to be much larger in 2004 and 2005. The reverse applies to the share of joint filers below 65 while the shares of head of household and single filers seem comparable across years. Comparing the numbers of 2004 and 2005 with other years corroborates the earlier impression – the discrepancies affect the joint filer and nonfiler categories only. Moreover, compared to other years, the share of non filers is about 20 percentage points larger while the share of all joint filers is about 20 percentage points lower. Lastly, the shares of singles and nonfilers are very similar to those of other years.

FILESTAT	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
1	33.43	33.84	33.66	33.63	**16.64**	**16.49**	34.78	35.41	35.21	35.17	34.14	34.02	33.4	33.15	32.98	32.67
2	1.89	1.68	1.67	1.6	**0.73**	**0.73**	0.84	0.88	0.97	1.02	0.97	1.01	1.02	1.06	1.12	1.13
3	4.21	3.08	3.05	3.03	**0.98**	**0.98**	1.54	1.6	1.62	1.61	1.63	1.7	1.83	1.9	2.04	2.05
4	4.28	4.76	4.83	4.87	4.56	4.59	4.61	4.24	4.25	4.16	4.21	4.19	4.24	4.14	4.11	4.09
5	20.59	18.43	18.12	17.69	17.09	16.83	18.1	18.27	18.72	18.44	18.5	18.3	18.43	18.79	18.86	19.06
6	35.6	38.2	38.66	39.19	**60.0**	**60.38**	40.12	39.6	39.23	39.6	40.54	40.78	41.07	40.96	40.89	40.99

Table 19: *Relative frequencies of FILESTAT in selected years (in %)*

Both of these limitations make the tax variables unsuitable for extending the state tax and transfer progressivity estimates to the episodes of the cash check episodes I am studying in this paper. First, I would ignore progressivity differences due to state tax credit variation prior to 2005. Second, the Census Bureau tax model might feature additional (undocumented) time variability in the tax variables it imputes for the ASEC dataset.

[48]See, for example, a note by Daniel Feenberg of TAXSIM available here: `http://users.nber.org/~taxsim/to-taxsim/cps/cps-feenberg.html`.

FHSV	Extended Estimation	
2010/11	2000-2002	2007-2009
New Hampshire	Wyoming	South Dakota
Florida	South Dakota	Texas
Alabama	New Hampshire	New Hampshire
Texas	Texas	Nevada
North Dakota	Florida	Wyoming
Wyoming	Nevada	Florida
South Dakota	Tennessee	Indiana
Louisiana	Indiana	Alabama
Nevada	Illinois	Tennessee
Illinois	Alabama	North Dakota
	North Dakota 12	Illinois 11
	Louisiana 16	Louisiana 17

Table 20: *The 10 most regressive states according to the baseline measure of tax and transfer progressivity (FHSV) and the extended estimation for 2001 and 2008. Underlined states in the baseline measure are not among the 10 most regressive states in the extended estimation but close runner-ups.*

E.6 Persistence of State Tax Policy

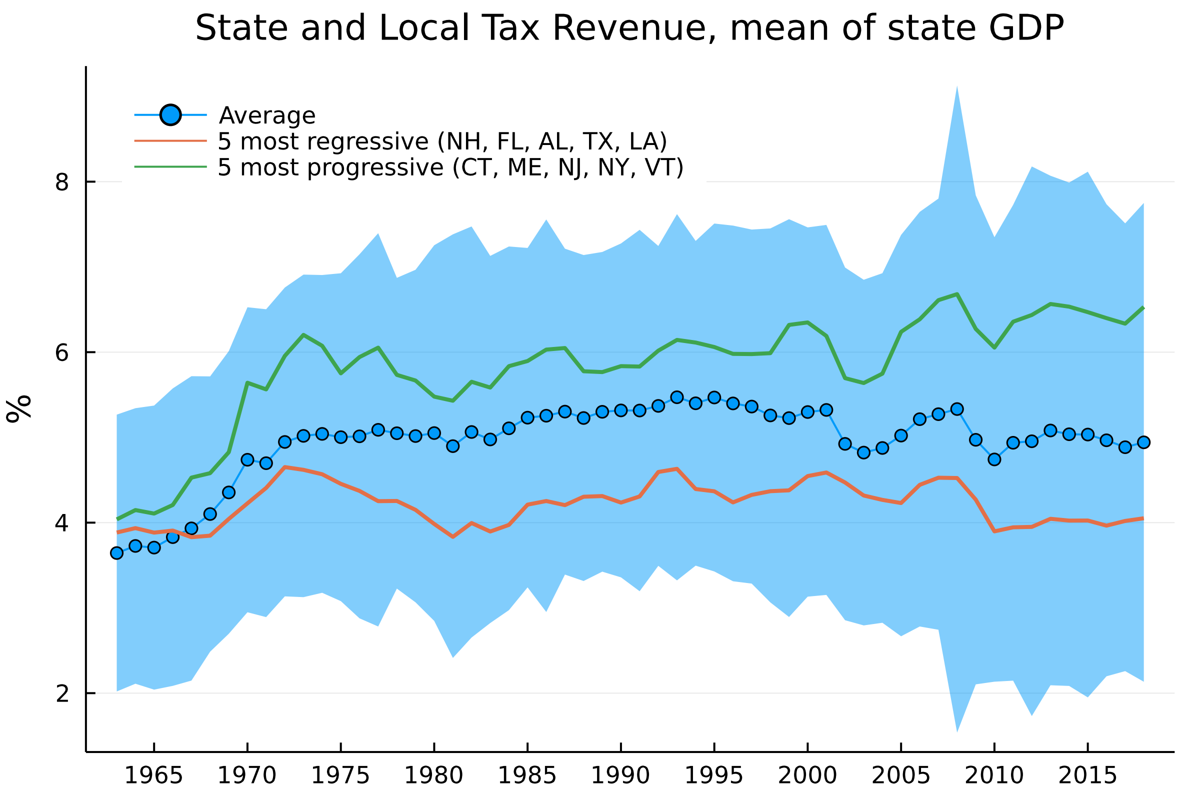

Figure 15: *Total state and local tax revenue as a share of state GDP. Taxes include personal and corporate income taxes, sales, excise and property taxes. Five most regressive and progressive states according to FHSV 2021 (except North Dakota which as sizable petroleum related revenues). Computed using data from the Census Bureau's Annual Survey of State and Local Government Finances and the Bureau of Bureau of Economic Analysis.*

F Estimating Earnings Risk using the linked ASEC

F.1 The CPS Rotating Panel

The Annual Social and Economic Supplement (ASEC) is part of the Current Population Survey (CPS). Due to the 4/8/4 design of the CPS, households included in ASEC are interviewed in two consecutive years. Figure 16 illustrates this point. Hence, using the moment conditions derived in section 7, I can use the linked ASEC dataset to compute the moments of a persistent-transitory earnings process under certain assumptions.

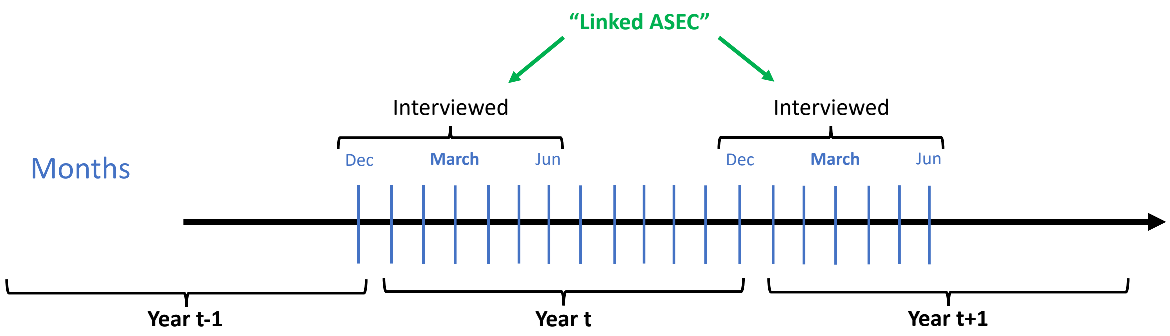

Figure 16: *Structure of the Linked ASEC within the CPS interview months*

F.2 Moment Conditions of a Permanent-Transitory Income Process

Suppose individual unpredictable log earnings $y_{i,t}$ follow the process described below; they are given as the sum of a transitory shock $\varepsilon_{i,t}$ which is iid normally distributed with variance σ_ε^2 and a persistent shock $\eta_{i,t}$ which is iid normally distributed with variance σ_η^2 and follows an AR1 process with persistence ρ.

$$y_{i,t} = z_{i,t} + \varepsilon_{i,t} \sim N(0, \sigma_\varepsilon^2) \tag{141}$$

$$z_{i,t} = \rho z_{i,t-1} + \eta_{i,t} \sim N(0, \sigma_\eta^2) \tag{142}$$

As shown in section 7, for a given value of the persistence parameter, $\overline{\rho}$, the error variances of this model σ_ε^2 and σ_η^2 can be estimated using the following moments of a two-period panel $(T = 2, N = large)$

$$\hat{\sigma}_\varepsilon^2 = \hat{var}(y_{i,t}) - \frac{1}{\overline{\rho}} \hat{cov}(y_{i,t}, y_{i,t-1}) \tag{143}$$

$$\hat{\sigma}_\eta^2 = \hat{var}(\Delta y_{i,t}) - 2\hat{var}(y_{i,t}) + \left(\frac{1-\overline{\rho}^2}{\overline{\rho}} + 2\right) \hat{cov}(y_{i,t}, y_{i,t-1}) \tag{144}$$

In many applications, it is common to add an individual fixed effect to the earnings process model presented here. However, I cannot do so due to data limitations – the ASEC linked panel only includes observations for two consecutive years. Thus, this modeling choice reflects the assumption that differences in initial conditions across US states are not a major determinant of state specific risk.

As time variability of the model parameters has been documented in US earnings data, I estimate the error variances over a longer time horizon.[49] Specifically, I estimate the parameters in two year frames and then average across a wider frame (e.g. from 1990 to 2007). This gives estimates $\hat{\sigma}^2_\eta$ and $\hat{\sigma}^2_\varepsilon$ for every state s and year frame t averaged over all observations in each state and years contained in a given frame. Accordingly, for each US state s, this estimation characterizes persistent and transitory earnings risk over a longer time horizon.

However, this approach to identification requires the persistence parameter to be constant across states $\rho = \overline{\rho}$, i.e. to be determined outside of the model, so the parameter space is restricted in one dimension. I pick a value of 0.95 for $\overline{\rho}$ which is similar to reported estimates used in the literature, for example by Krueger, Mitman, and Perri (2016) and I present the sensitivity of the innovation variance estimates with respect to changes in this parameter in appendix F.4.

F.3 Results

F.4 The Sensitivity of Earnings Risk Estimates with respect to $\overline{\rho}$

The sensitivities of the innovation variance estimates $\hat{\sigma}^2_\varepsilon$ and $\hat{\sigma}^2_\eta$ with respect to the persistence parameter $\overline{\rho}$ are given as:

$$\frac{\partial \hat{\sigma}^2_\varepsilon}{\partial \overline{\rho}} = \underbrace{\frac{1}{\overline{\rho}^2}}_{>0} \underbrace{\widehat{cov}(y_{i,t}, y_{i,t-1})}_{?} \tag{145}$$

$$\frac{\partial \hat{\sigma}^2_\eta}{\partial \overline{\rho}} = \underbrace{-\left(1 + \frac{1}{\overline{\rho}^2}\right)}_{<0} \underbrace{\widehat{cov}(y_{i,t}, y_{i,t-1})}_{?} \tag{146}$$

Hence, as these equations illustrate, the size and magnitude of changing ρ on the parameter estimates depends on the sign and magnitude of the empirical covariance $\widehat{cov}(y_{i,t}, y_{i,t-1})$ in all state and year windows. For example, if it is uniformly positive, then

$$\frac{\partial \hat{\sigma}^2_\varepsilon}{\partial \overline{\rho}} > 0 \tag{147}$$

$$\frac{\partial \hat{\sigma}^2_\eta}{\partial \overline{\rho}} < 0 \tag{148}$$

I illustrate the effect of minor variations of this fixed parameter at its given value and the em-

[49] See Gottschalk and Moffitt (1994), Krueger and Perri (2006) and Heathcote, Storesletten, and Violante (2010).

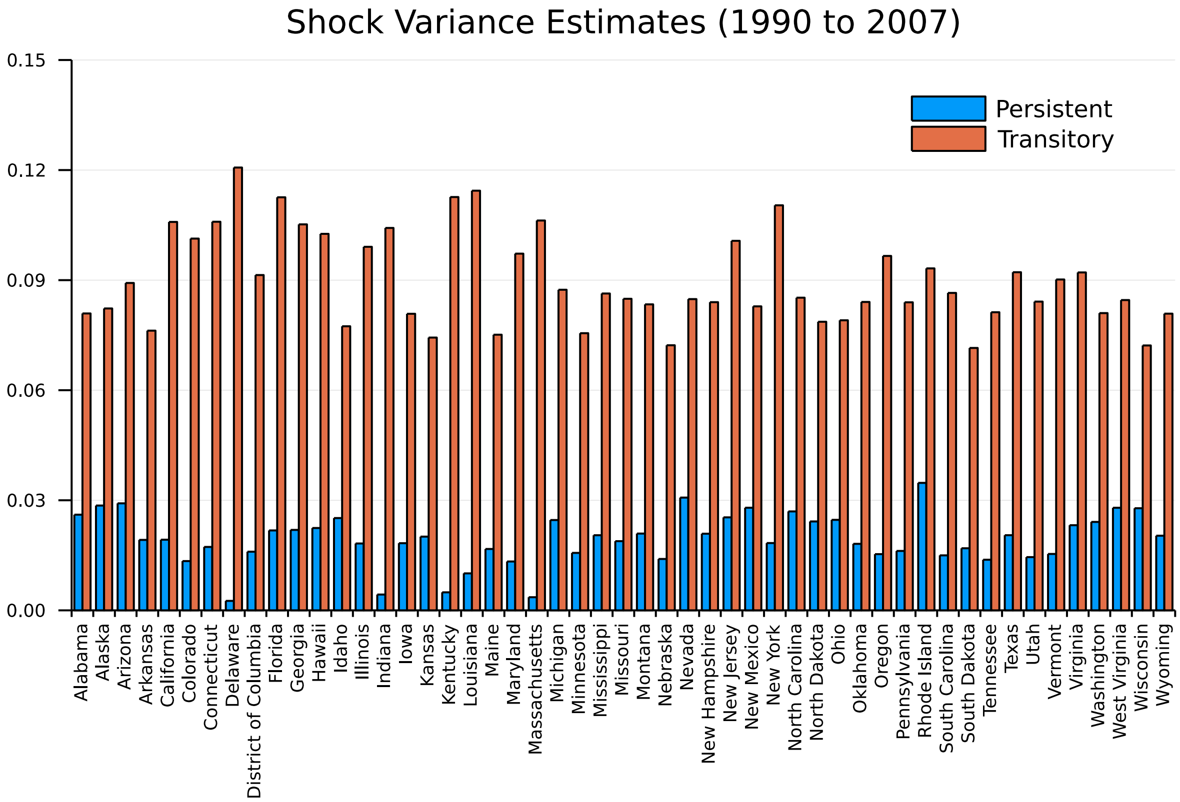

Figure 17: *Error Variances Estimates of a Transitory Persistent Earnings Process (as described in section 7.). Computed from linked ASEC data as described in the preceding section.*

pirical value of $cov(y_{i,t}, y_{i,t-1})$ in figure 18.

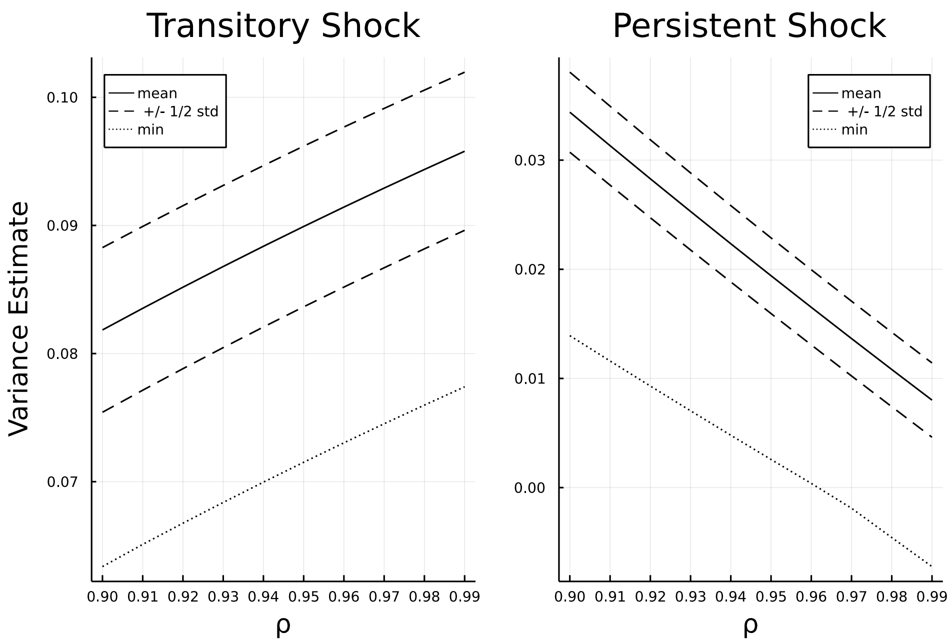

Figure 18: *Evaluating the sensivitiy of earnings variance to changes in the exogenous parameter ρ*

For values $\bar{\rho} > 0.96$ the resulting variance of the persistent shock, $\hat{\sigma}_\eta^2$ becomes negative due to the magnitude and sign of the empirical covariances. However, for $\bar{\rho} = 0.95$, which I choose for my estimation, both error variances are positive.

F.5 Predictable Earnings Components

As is common in the literature, I compute the unpredictable earnings $y_{i,t}$ of each observation as the residuals of the following regression:

$$\log \tilde{y}_{i,t} = \beta_0 + \beta_1' X_{i,t} + \epsilon_{i,t} \tag{149}$$

where $\tilde{y}_{i,t}$ denotes reported labor earnings, β_0 absorbs year effects and X are observable characteristics such as household head age, age square education, gender, race, marital status and include interactions between age and industry occupation as well as education. Table 21 shows the complete list of all regressors and their coefficient estimates.

	Log wage, salary income (year t)	Log wage, salary income (year t+1)
	(1)	(2)
Constant	8.859***	8.923***
	(0.001)	(0.001)
female	-0.391***	-0.380***
	(0.000)	(0.000)
race: black	-0.059***	-0.061***
	(0.000)	(0.000)
race: other	-0.046***	-0.041***
	(0.000)	(0.000)
not married	-0.061***	-0.063***
	(0.000)	(0.000)
age	0.055***	0.055***
	(0.000)	(0.000)
age2	-0.001***	-0.001***
	(0.000)	(0.000)
education: high school and some college	0.437***	0.394***
	(0.000)	(0.000)
education: at least undergrad degree	0.716***	0.693***
	(0.001)	(0.001)
employment: industry	-0.000***	-0.000***
	(0.000)	(0.000)
employment: occupation	-0.000***	-0.000***
	(0.000)	(0.000)
age $\times$ high school and some college	-0.003***	-0.002***
	(0.000)	(0.000)
age $\times$ at least undergrad degree	-0.002***	-0.002***
	(0.000)	(0.000)
age $\times$ employment: occupation	-0.000***	-0.000***
	(0.000)	(0.000)
year: 1991	0.026***	
	(0.000)	
year: 1992	0.068***	0.039***
	(0.000)	(0.000)
year: 1993	0.094***	0.068***
	(0.000)	(0.000)
year: 1994	0.119***	0.087***
	(0.000)	(0.000)
year: 1995		0.115***
		(0.000)
year: 1996	0.168***	
	(0.000)	
year: 1997	0.197***	0.169***
	(0.000)	(0.000)
year: 1998	0.235***	0.211***
	(0.000)	(0.000)
year: 1999	0.268***	0.248***
	(0.000)	(0.000)
year: 2000	0.309***	0.276***
	(0.000)	(0.000)
year: 2001	0.344***	0.309***
	(0.000)	(0.000)
year: 2002	0.362***	0.334***
	(0.000)	(0.000)
year: 2003	0.391***	0.360***
	(0.000)	(0.000)
year: 2004	0.425***	0.390***
	(0.000)	(0.000)
year: 2005	0.431***	0.421***
	(0.000)	(0.000)
year: 2006	0.431***	0.429***
	(0.000)	(0.000)
year: 2007		0.401***
		(0.000)
Estimator	OLS	OLS
N	393,965,081	386,111,372
R^2	0.345	0.346

Table 21: *Computing unpredictable earnings changes in the linked ASEC sample. Note: for year t, 1995 is not included since observations from 1995 cannot be linked across years. The same applies to year t+1 for 1996. Since 1991 and 2007 are the first and last years, they are missing from t+1 and t.*