ESSAYS ON MACROECONOMICS WITH HETEROGENEOUS REGIONS

By

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Abstract

This dissertation studies macroeconomics with regional heterogeneity in three general dimensions. First, it documents some novel empirical patterns of regional heterogeneity (in Chapter 1, 2, 3). Second, these empirical facts are used to identify key economic forces underlying theoretical models (in Chapter 1 and 3). Third, aggregate implications of regional heterogeneity are also studied (in Chapter 1).

In the first chapter of this dissertation, I highlight time-varying regional risk and federal fiscal transfer policy as two competing forces driving regional risk sharing over the business cycle and in turn quantify their impacts on aggregate fluctuations. I find that during an economic downturn, increased regional risk worsens risk sharing and amplifies the impact of aggregate productivity shocks. However, state-contingent federal government transfers provide additional risk sharing and help stabilize the aggregate economy, by providing insurance to the regions that need it the most.

In the second chapter (joint with Noah Williams), we first estimate a quarterly dataset for state-level aggregates by building a novel empirical framework that allows for mixed-frequency raw data with measurement errors. We then apply this dataset to study the monetary policy effects at the state levels. We find that states behave remarkably *homogeneous* with each other in their responses of output and price to an unanticipated monetary policy shock.

In the third chapter (joint with Noah Williams), we use the state-level quarterly dataset to analyze the impact of unexpected changes in federal personal and corporate income taxes. We find substantial *heterogeneity* in the impact of federal fiscal policy across states, with more than half having no significant response to the tax cuts. In addition, less capital-intensive states have larger responses to corporate tax cuts. Although puzzling in standard models, a model with corporate and non-corporate sectors is consistent with this evidence. Overall, our results suggest the importance of variation

and reallocation across states in evaluating federal policy.

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Chapter 1

Regional Risk and Aggregate Fluctuations

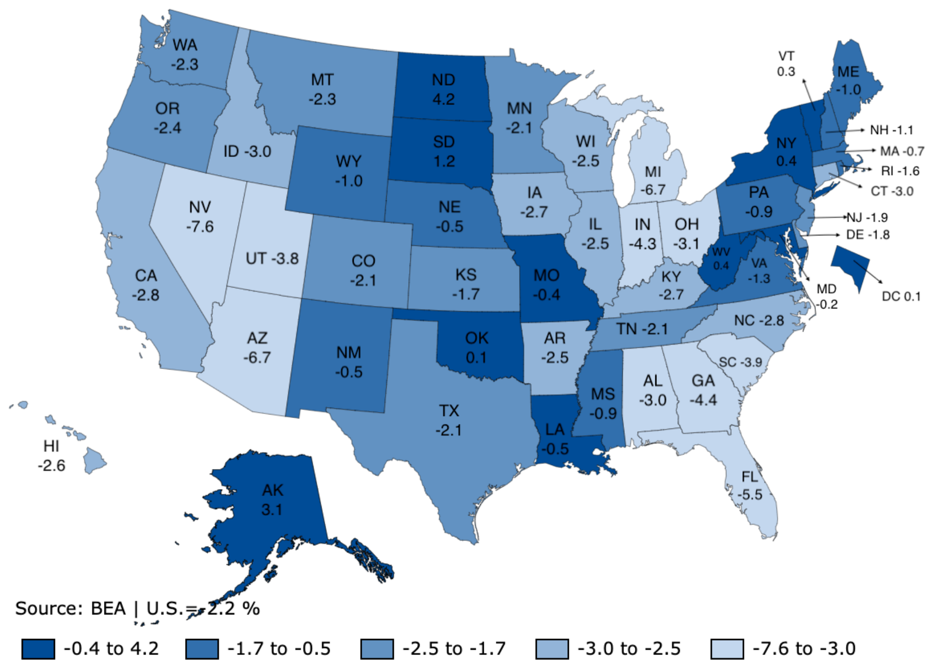
1.1 Introduction

The Great Recession hit the U.S. economy hard, but its magnitudes varied substantially across states. From the peak year of 2007, to the trough year of 2009, annual per capita U.S. GDP growth rate was –2.2%, whereas state-level growth varied from –7.6% to +4.2% (see Figure 1 for growth rates in this period for all the U.S. states). The economy of Nevada, the worst performing state, plunged from a positive pre-crisis growth rate all the way to –8% in 2009; while North Dakota maintained positive growth throughout the crisis period, and it recovered very quickly afterwards.

This dispersion in economic performance was likely to be driven by more than one factor. For example, while the housing market crisis was at the center of Nevada's fall, the "shale oil revolution" served as a cushion for the North Dakota economy. Beyond differences in output growth, regional heterogeneity also exists in other dimensions, such as the housing market, credit market, and labor market. In light of these complications of regional heterogeneity, in this paper I follow a standard approach in the heterogeneous-agent macroeconomic literature by characterizing regional heterogeneity with idiosyncratic shocks to regional income (GDP or personal income) in the empirical section, and to regional total factor productivity (TFP) in the model section. The principal goal of this study is to understand the dynamics of the distribution of these regional shocks, and how they matter for aggregate fluctuations.

There are reasons why focusing on regional heterogeneity is necessary and important. First, an emerging strand of macro literature turns to "regions," such as states, counties,

Figure 1: Annual Growth Rate of Per Capita GDP by State: 2007-2009



Notes: This picture is generated by the BEA GDP and Personal Income Mapping tool. Dark areas had stronger per capita GDP growth rates than light ones, as evident from the legend. The growth rates are calculated as the annualized compound growth rates between the peak year of 2007 and trough year of 2009 during the recent recession.

MSAs, and zip-code areas, to address classic macro questions. These studies highlight the importance of regions as units of empirical analysis motivated by the fact that many economic variations stem from the regional level, for example the housing market and local government spendings. These heterogeneities provide identification strategies that are not available by replying solely on time series data. In the same spirit of this literature, this paper identifies new features of the regional data, and argues that they provide new insights into the aggregate business cycle fluctuations. Second, in the U.S. system, some federal policies are administered at the state or local level. As the main policy focus of this paper, part of the federal fiscal transfers, like unemployment insurance benefits, are made through separate state-level programs.[1] To better understand these policies, it's necessary to look beyond the aggregate, and instead, to make analysis at the regional level.

In the first half of this paper, I empirically explore one question: what is the distributional pattern of regional shocks in the U.S. economy? To address this question, I model the regional income process as being driven by two uncorrelated persistent shocks: one regional, and the other aggregate. The conditional variance of the former is allowed to be time varying, to capture the possibility of time-variation in regional risk. Regional consumption fluctuations are also associated with these two primitive shocks through two time-specific parameters that denote the sensitivity of consumption to either income shock. I apply a dynamic-panel GMM estimation to this system and draw two main findings from this exercise.

First, regional risk, defined as the conditional standard deviation of idiosyncratic shocks to U.S. state-level income growth, is strongly countercyclical. In the baseline estimation, it increases by roughly 40% (from 0.0197 to 0.0274) as the macroeconomy moves from normal times to NBER recession periods. This countercyclicality is robust to using an exactly identified vs. overidentified approach, or using growth rate data

[1] See Fischer (2017) for a detailed account of the federal-state partnership on unemployment insurance in US.

vs. detrended data. From this perspective, this paper adds to the literature on the implications of risk or uncertainty at the micro level. Previous studies used microdata at the household, firm or industry level to identify time-varying cross-sectional risk. For example, Storesletten et al. (2004) estimate that idiosyncratic labor market risk is both persistent and strongly countercyclical; Guvenen et al. (2014) show the skewness component of uncertainty in idiosyncratic earnings. Ravn and Sterk (2017) and McKay (2017) show that these dynamics of idiosyncratic risk at the household level have strong implications for aggregate consumption fluctuations during the Great Recession. Bloom et al. (2018) establish empirical evidence that the dispersions of plant- and industry-level innovations to TFP, or in their language "micro uncertainty," rise sharply in recessions, which they argue through a model is a key driver of business cycle fluctuations. Differing from these studies, I aim to uncover the implications of time-varying *regional* risk on aggregate fluctuations, addressed in the second half of this paper.

Second, regional risk sharing, defined as the negative of pass-through of regional income shocks to consumption, is high but still imperfect; furthermore, it does not vary over the business cycle.[2] In particular, on average 70%–80% of regional income shocks are smoothed away, indicating a high level of risk sharing across regions. This is consistent with the estimates of the regional risk sharing literature, e.g. Asdrubali et al. (1996), Del Negro (2002) etc. The fact that the degree of risk sharing across regions doesn't go down during recessions, however, is new to the literature and puzzling. As is well known, incomplete markets and credit constraints impede full insurance of regional economic shocks, especially so during a recession when the regional risk is higher and credit constraints are tighter, making it more difficult to provide risk sharing through

[2] Hoffmann and Shcherbakova-Stewen (2011) uses aggregate GDP growth as an indicator for "business cycle" and find that interstate consumption risk sharing increases in booms and decreases in recessions. However, when using NBER recessions as the indicator, which this paper does, the cyclicality disappears. While there's a disagreement on which indicator is better, the two papers have very different focuses. The former highlights the role of small businesses that are exposed to aggregate shocks, which are better characterized by aggregate GDP growth; my paper highlights the role of federal government fiscal transfer pattern that is only different in "official" economic recessions, i.e. NBER recessions. Nonetheless, the author suggests a cautionary tone of business cycle fluctuations in regional risk sharing.

the asset market (Berger et al., 2019; Dávila and Philippon, 2017). This contradiction, therefore, points to forces at play fostering risk sharing across regions during recession periods.

I highlight the role of federal fiscal policies, primarily on transfers and taxes, in providing insurance against regional shocks during recessions.[3] This is not the first study to point out that an integrated tax and transfer system can help mitigate local shocks; for example, Sala-i Martin and Sachs (1991) and Asdrubali et al. (1996) estimate the magnitude of state-level risk shared through an integrated fiscal system. However, the new finding in this study is that federal fiscal transfers are contingent on local economic shocks, but only during national recessions. During the Great Recession, federal net fiscal transfer (transfer less tax) growth across U.S. states was negatively correlated with state GDP growth, implying an effective "state-contingency" in federal fiscal policy. Cross-sectional regression results demonstrate that a one percentage point lower GDP growth rate during the recession was associated with at least 0.33 percentage points higher net fiscal transfer growth. However, in the years leading to the Great Recession, this correlation was nonexistent. To understand these findings, I first separately study the geographic distribution of federal transfers and taxes. I find that the former is state-contingent only during recessions while the latter is so during both recession and normal times. I then decompose the total federal government transfer growth by category. I find indicative evidence that the state-contingent pattern of the transfer policy is driven by the unemployment insurance surge during recessions, which is state-contingent by nature, unlike other components like retirement benefits or disability insurance.

In the second half of this paper, I build a model and ask: To what extent have these patterns of regional shocks contributed to *aggregate* fluctuations? And what role do redistributive federal transfers play? I provide a positive analysis of the implications

[3] In the literature, factor mobility, other public policies, and multi-regional firms, among others, are also studied as means of regional risk sharing. See Blanchard and Katz (1992); Hurst et al. (2016); Giroud and Mueller (2019) etc.

of regional shocks for aggregate fluctuations. In particular, I study how countercyclical regional risk and federal fiscal transfers interact with aggregate productivity shocks in shaping aggregate fluctuations in output. To do so, I build a multi-region New Keynesian economy with an incomplete asset market, credit constraints, time-varying regional risk, and federal government fiscal transfers. I solve the model using the algorithm proposed by Winberry (2018). In particular, I approximate the joint distribution of regional productivity shocks and asset holdings with a flexible parametric family and reduce the state-space from infinite dimension to a few parameters that fully characterize the distribution. Key parameters of the regional and aggregate productivity processes are estimated through the simulated method of moments (SMM), to match the estimates in the empirical section.

First, I investigate the impulse responses of consumption dispersion and aggregate output to the two aggregate shocks: an aggregate productivity shock and a regional risk shock. Upon realization of a negative productivity shock, consumption dispersion rises; it does so even more if the economy also draws a positive regional risk shock. This is due to the fact that more regions are constrained at the borrowing limit. However, when comparing an economy that has active state-contingent fiscal transfers to another that doesn't, the responses of the former are much muted, indicating the power of fiscal policy in providing consumption insurance during an economic downturn. The impact of aggregate productivity shocks on aggregate output fluctuations is amplified if the regional risk goes up concurrently, due to the stronger precautionary saving motives that lower aggregate demand. By restoring consumption risk sharing, state-contingent federal government transfers effectively provide insurance to the regions that need it the most, as these regions happen to have the highest marginal propensity to consume.

Second, to separately quantify the roles of time-varying regional risk and fiscal transfers, I focus on a particular episode, the Great Recession. I use the data to estimate the series of TFP shocks during this period and feed them to the models. I compare the baseline economy (with contingent transfers, negative productivity shocks, and increased regional risk), with three counterparts: the data, counterfactual economies shutting down each channel, and a counterfactual economy with complete markets. The baseline economy accounts for around 80% of the actual drop in aggregate GDP from peak to trough during the recession, and the fact that regions don't share risk perfectly accounts for around 23% of the total decline. The maximum drop in aggregate GDP in the counterfactual economy without an increase in regional risk is 0.6 percentage points lower than the baseline, while that in the counterfactual economy without state-contingent transfers is 0.4 percentage points higher than the baseline, suggesting that the amplifying magnitude of time-varying regional risk is slightly higher than the dampening effect of fiscal transfers.

Overall, this paper highlights time-varying regional risk and federal fiscal transfers as two competing forces in driving regional risk sharing and separately quantifies their implications for aggregate fluctuations. The remainder of this paper is organized as follows. Section 1.2 documents the related literature. Section 1.3 discusses the data, empirical strategy and main results. Section 1.4 formally presents the model and defines the equilibrium. In Section 1.5, I quantify the aggregate impact of regional shocks. Section 1.6 concludes.

1.2 Related Literature

First, this paper is broadly related to a recently growing literature on leveraging regional heterogeneities to make inferences on the mechanisms underlying aggregate fluctuations, especially the Great Recession (Mian et al., 2013; Mian and Sufi, 2014), transmission of monetary policy (Beraja et al., 2019), and effectiveness of fiscal policy (Nakamura and Steinsson, 2014; Dupor et al., 2019; Chodorow-Reich, 2019; Liu and Williams, 2019). These studies highlight the importance of regions as units of empirical analysis not only because of the limited availability of data at the household level, but also due to the fact that many economic variations come from the regional level, such as the housing market and local government spendings. Motivated by, but different from these studies, this paper performs a systematic empirical analysis of the "risk" facing regional economies, using a long panel dataset instead of focusing on just one particular episode.

Second, my empirical analysis on cross-state risk sharing is related to the literature on risk sharing across countries and across regions within a country. There exists a large literature in international macroeconomics focusing on international risk sharing. Backus et al. (1992) and Backus and Smith (1993), among others, test for and strongly reject perfect consumption risk sharing across countries. A number of explanations for this have been provided in the literature, notably asset market incompleteness and costs of trading goods (Backus and Smith, 1993; Obstfeld and Rogoff, 2000; Corsetti et al., 2008; Fitzgerald, 2012). Regarding within-border risk sharing, most of the previous studies confirm that there's imperfect but better risk sharing across states than across national borders (Asdrubali et al., 1996; Crucini, 1999; Athanasoulis and Wincoop, 2001; Devereux and Hnatkovska, 2019). In addition to the linear regression methods used in most of the previous studies, this paper incorporates the dynamic panel GMM estimation framework, common in the household-level analysis (Blundell and Bond, 1998; Storesletten et al., 2004; Blundell et al., 2008) that is able to separate regional shocks from aggregate shocks and jointly estimate regional risk and risk sharing. Moreover, this paper also investigates the time variation in regional risk sharing, in particular comparing recessions and normal periods. Lustig and Van Nieuwerburgh (2010) identify housing collateral scarcity as an important source of time variation in risk sharing across U.S. MSAs, suggesting worse risk sharing arrangements during a time when housing collateral is scarce, such as the Great Recession. I empirically find no worse risk sharing during recessions, implying that there are other channels at work.

Third, this paper adds to the literature examining how public policy neutralizes the adverse impacts of local economic shocks, including explicit fiscal transfers and redistributive taxation (Farhi and Werning, 2016, 2017; Beraja, 2019) and mechanisms that may be implicit (Hurst et al., 2016). I innovate by providing new evidence that the "state-contingency" of federal fiscal transfers is only evident during recessions but not normal times, which proves to be crucial in reconciling the regional risk and risk sharing patterns. Additionally, I build a positive framework and show that this special fiscal arrangement has important implications for regional risk sharing patterns over the business cycle and the aggregate fluctuations during an economic downturn, adding to the normative analysis of fiscal unions by Farhi and Werning (2017), and broadly consistent with the implications of a central fiscal authority proposed in Evers (2015). Notably, the channel emphasized here is different from the conventional "automatic stabilizing" effects of the tax-and-transfer system, which dictates that increasing transfers and decreasing taxes help stabilize the aggregate economy during a recession.[4] Whereas in the channel studied in my framework, the U.S. fiscal system effectively stabilizes the aggregate fluctuations by stabilizing the regional economy due to the its "state-contingency" during recessions, that is, not only are the total transfers relevant, but also their geographic distributions.

Fourth, this paper is also related to New Keynesian models with heterogeneous agents, especially with heterogeneous regions. Heterogeneous-Agent New Keynesian (HANK) models incorporate household heterogeneity and market incompleteness in macro studies, providing us new insights on economic fluctuations and transmission of monetary policy (Werning, 2015; Krueger et al., 2016; Guerrieri and Lorenzoni, 2017; Kaplan et al., 2018; Kaplan and Violante, 2018). However, as mentioned earlier, heterogeneity is better modeled at the regional level in some economic contexts. Jones et al. (2018) evaluate the importance of regional credit shocks in generating the macroeconomic dynamics across regions and in the aggregate; Beraja et al. (2019) argue that regional data contain important information that helps discipline models of aggregate fluctuations. However, the log-linearization approach taken by these papers would likely miss the key implications of imperfect risk sharing.[5] Departing from this literature, my

[4]See McKay and Reis (2016) for an extensive study of the impact of most of the major automatic stabilizers on the U.S. economy.

[5]In fact in Beraja et al. (2019), the log-linearized regional economies aggregate up to a representative

study focuses on the role of dispersion in regional shocks in shaping the risk sharing and aggregate fluctuations, which naturally calls for a global solution method. I build on the solution techniques of Reiter (2009) and Winberry (2018) and apply them to a heterogeneous regions New Keynesian model, which, to my best knowledge, is the first paper to do so.

Lastly, I allow for inter-regional trade linkages in the quantitative model, which are key and common in spatial economics, see Desmet and Rossi-Hansberg (2014); Desmet et al. (2018); Caliendo et al. (2018); Adão et al. (2019) and the review paper Redding and Rossi-Hansberg (2017). Trade is identified as an important channel in propagating local demand shocks during the Great Recession in Stumpner (2019). Obviously deviating from this literature, I study the dynamic implications of region-level shocks in a multi-region business cycle framework, while the spatial economics literature mostly analyzes within a static setup.

1.3 Empirics: Regional Risk and Regional Risk Sharing

A region is defined as a U.S. state in the empirical analysis. In principle, one can study beyond a state and conduct analysis at the MSA, county or even zipcode level. There are two reasons for choosing a state as the unit of analysis. First, standard macro data are hard to obtain even at the state level, and much more so at a more disaggregate level. For example, GDP is available from BEA Regional Accounts at county, MSA, and state levels, but only for a fairly short sample for the former two; state-level consumption is only available from BEA in the post-1997 period; and state-level consumer price index is not obtainable and has to be constructed by other means. Second, as will become clear soon, fiscal integration is a crucial ingredient for this study, and some federal fiscal

economy where the aggregate variables are independent of cross-sectional considerations; they only matter in the sense that regional data help identify the model parameters.

transfers are administered at the state level, such as the federal unemployment benefits. Therefore, to analyze at the state level well suits this study.

This section begins with a description of data together with some summary statistics. After that, the main estimation strategies and results of the empirical section are discussed. I then compare some of the results with those, if available, that obtain from conventional regressions as a validation analysis. A particular channel, the federal government transfer system, is discussed at length on how it fits well in the context of this study, and what new insights in may add to the literature.

1.3.1 Data

The main used in the empirical exercise are the state-level GDP, consumer price, personal income, disposable personal income, consumption, federal fiscal tax and transfers, house prices; together with their national counterparts. Throughout the empirical analysis, I transform raw data into their real per capita terms, where state-level population data can be accessed from U.S. Census Bureau Annual Estimates of the Population for the U.S. and States. Estimates for 2010-2018 reflect Census Bureau midyear state population estimates available as of December 2018.

The BEA Regional Economic Accounts manage most of the state-level data that this paper uses. Most of them are available only at the annual frequency, although some of them can be accessed in a quarterly frequency in a short time series, such as GDP. The consumption dataset is worth a few more words here. Since BEA only maintains a short state-level consumption sample, available only after 1997, I take the adjusted state retail sales data, coming from a magazine survey that dates back to 1960, as the main measure for consumption before 1997, which is the best available proxy for a long panel of state-level consumption. Its drawback is nonetheless predictable, namely the measurement errors may be large for the pre-1997 sample period. This data feature is taken into account in the following empirical analysis, as I elaborate below.

I've also used the annual state-level house price data from the U.S. Federal Housing Finance Agency and the annual state-level household debt data from the Federal Reserve Bank of New York. Details on the data source and construction procedures are relegated to Appendix A.1.

1.3.2 Descriptive Evidence

Two objectives of the empirical study are to figure out: 1) the time pattern of spatial distribution of idiosyncratic shocks, and 2) the time pattern of the degree of risk sharing across regions. Before the estimation exercise where I formally put a structure on the income growth process and separately identify regional and aggregate shocks, it's useful to present some descriptive data facts to guide intuitions and to compare with the existing literature. In particular, I provide some data facts on cross-regional dispersions of income and consumption, and calculate the consumption correlations by state.

Cross-Regional Dispersions

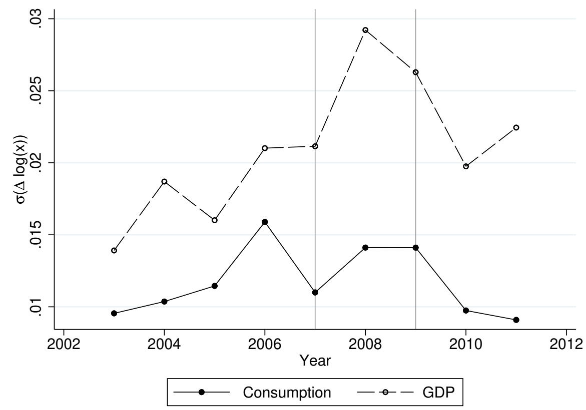
To visualize the pattern of distribution of idiosyncratic shocks, a natural summary statistic is the cross-sectional dispersion of regional output or personal income growth, denoted as $\sigma_t(\Delta \log y_{i,t})$. Regarding consumption risk sharing, in the extreme case of perfect risk sharing when there is a complete set of state-contingent securities available to regional households, Backus and Smith (1993) famously point out that relative consumption growth should be perfectly correlated with the change of real exchange rates. If the dispersion of inflation rates is low, which the data support, consumption growth rates should be equalized across regions. Hence the dispersion of consumption growth, $\sigma_t(\Delta \log c_{i,t})$, serves as a useful and simple benchmark for measuring risk sharing.

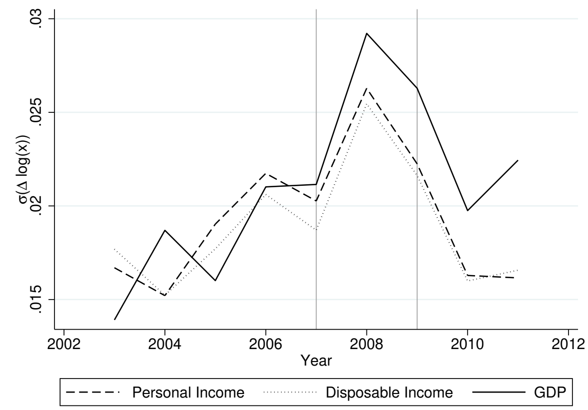
The left panel of Figure 2 displays the cross-sectional dispersions of growth in consumption against GDP, and the right panel displays those of personal income, disposable income and GDP growth, both for the 10-year period covering the Great Recession. The dispersion in GDP growth rates rose sharply and reached peak during the recession, and so did that of (disposable) personal income growth rates. This larger heterogeneity in regional growth implies higher regional risk during the Great Recession, if we think of regional shocks as orthogonal to aggregate ones. As will be clear later, this statistic does not map one for one to regional risk as it includes the long-run difference across regions. However, it doesn't affect our interpretation of the time variation, as the long-run component doesn't vary over time. The fact that GDP growth dispersion is slightly larger than that of personal income and disposable income indicates some form of income smoothing across regions. And I'll emphasize the federal fiscal transfers as the main channel in Section 1.3.5.

Despite the rise in dispersion of regional income shocks, dispersion of regional consumption did not increase as much in the recession years; in fact, regional consumption inequality in 2007-2009 stayed consistently below the pre-recession year of 2006. Loosely speaking, this seems to suggest that regional risk sharing has stayed strong in the Great Recession. It turns out that this regional consumption inequality finding echoes with studies on the business cycle patterns of household consumption inequality. For example, Parker and Vissing-Jorgensen (2009), Krueger et al. (2010) and Perri and Steinberg (2012) find that consumption inequality tends to increase much less than earnings and income inequality during recessions.

Taken together, the cross-regional dispersion plots suggest that the economy experienced higher regional risk during the Great Recession, meanwhile the regional risk sharing didn't worsen. When the same figures are plotted using the whole sample in Figure 26 in the Appendix, I find these findings still hold: the dispersion of income measures was consistently higher during recessions, whereas that of consumption was mixed.

Figure 2: Cross-Sectional Dispersions around the Great Recession





Notes: Left: cross-sectional conditional standard deviation of consumption and GDP growth across regions for each year. Right: cross-sectional conditional standard deviation of personal income growth, disposable income growth, and GDP growth. All series are in real per capita terms. The grey vertical lines represent the start and end of the Great Recession.

Consumption Correlations

An alternative perspective on regional risk sharing dates back to Backus et al. (1992) (BKK), who document the "consumption correlation puzzle" across countries. They find that international correlations in consumption are lower than that in output , which is confirmed by subsequent studies on international risk sharing. The BKK puzzle indicates poor risk sharing across countries, as had it been good, the growth or detrended values of consumption should be much more correlated than those of output.

Motivated by these previous studies, I present in Table 1 the correlation statistics (consumption growth, output growth, personal income growth) between each state and the aggregate. The pre-1997 consumption dataset is more noisy than the post-1997 one, and for this descriptive analysis I select the 1997-2017 sample period. The consumption correlations are high among U.S. states, especially when compared to those of cross-country pairs. This accords with the comparison studies of regional and international risk sharing (Crucini, 1999; Devereux and Hnatkovska, 2019).

The second column shows the correlation of state-level consumption growth with the aggregate. With only a few exceptions, say North Dakota, consumption is highly correlated with the aggregate for most of the states; and a large number of states have correlation values greater than 0.7. For GDP it's the opposite: while GDP in some states are strongly correlated with the aggregate, for example in California this correlation is close to 1, this statistic is below 0.5 or even close to 0 for almost half of the states. State and national correlations in personal income growth are on average larger than those in GDP, but still consistently below those in consumption. Columns 5-6 present the same statistics in BKK, the correlations of consumption relative to income. In BKK, this ratio is consistently below 1 for all the countries (relative to U.S.) with an average value of 0.49; however, in the regional analysis here, it's almost always close to or larger 1, regardless of our choice of income (output or personal income). Moreover, this finding is robust to using detrended data instead of growth.

1.3.3 GMM Estimation

Instead of solely focusing on the summary statistics, an alternative approach focuses on the sensitivity of consumption to idiosyncratic income shocks as a measure of risk sharing, both in the household (Blundell et al., 2008; Jappelli and Pistaferri, 2010, 2011) and regional risk sharing literature (Asdrubali et al., 1996; Crucini, 1999). The key idea is that when there's full consumption insurance, idiosyncratic income shocks should not matter for consumption decisions, although they might be influenced by aggregate shocks. In the regional context, a simple way to see the degree of regional risk sharing is to regress regional consumption growth rates (relative to aggregate) on idiosyncratic income (output or personal income) growth. The coefficient attached to idiosyncratic income growth should be zero when risks are shared perfectly. However, this traditional OLS approach is unable to precisely separate regional shock from aggregate shocks.

Because of this, in my baseline estimation framework I put some structure on the income and consumption process, similar to the household consumption insurance literature, and assume that the sole relevant source of uncertainty faced by each region is

Table 1: Correlations between State and the Aggregate

State Abbrev. (i)	$Corr(\hat{c}_i, \hat{c})$	$Corr(\hat{y}_i, \hat{y})$	$Corr(\hat{pi}_i, \hat{pi})$	$\frac{Corr(\hat{c}_i,\hat{c})}{Corr(\hat{y}_i,\hat{y})}$	$\frac{Corr(\hat{c}_i,\hat{c})}{Corr(\hat{pi}_i,\hat{pi})}$
AL	0.751	0.766	0.661	0.980	1.136
AZ	0.629	0.817	0.49	0.771	1.285
AR	0.772	0.475	0.606	1.624	1.273
CA	0.887	0.948	0.758	0.936	1.170
CO	0.814	0.692	0.489	1.176	1.662
CT	0.766	0.748	0.636	1.024	1.204
DE	0.762	0.322	0.569	2.369	1.340
FL	0.829	0.793	0.703	1.045	1.179
GA	0.839	0.804	0.657	1.044	1.276
ID	0.794	0.841	0.601	0.944	1.321
IL	0.902	0.883	0.751	1.022	1.201
IN	0.822	0.738	0.727	1.113	1.131
IA	0.794	0.646	0.596	1.229	1.333
KS	0.938	0.570	0.425	1.645	2.204
KY	0.797	0.490	0.807	1.627	0.988
LA	0.641	0.179	0.475	3.585	1.350
ME	0.840	0.690	0.810	1.216	1.036
MD	0.899	0.567	0.798	1.586	1.128
MA	0.905	0.856	0.734	1.057	1.234
MI	0.777	0.756	0.657	1.027	1.183
MN	0.791	0.809	0.796	0.978	0.994
MS	0.761	0.398	0.393	1.912	1.936
MO	0.644	0.695	0.855	0.926	0.753
MT	0.697	0.601	0.515	1.160	1.354
NE	0.816	0.214	0.496	3.816	1.643
NV	0.547	0.720	0.470	0.759	1.164
NH	0.908	0.763	0.814	1.191	1.116
NJ	0.817	0.814	0.756	1.003	1.080
NM	0.507	0.270	0.456	1.880	1.112
NY	0.690	0.381	0.488	1.809	1.414
NC	0.749	0.677	0.691	1.106	1.084
ND	0.094	-0.074	0.285	-1.269	0.328
OH	0.801	0.761	0.780	1.053	1.028
OK	0.791	0.362	0.312	2.188	2.535
OR	0.834	0.402	0.668	2.077	1.249
PA	0.849	0.682	0.732	1.245	1.160
RI	0.769	0.567	0.704	1.357	1.093
SC	0.835	0.732	0.814	1.142	1.026
SD	0.701	0.133	0.43	5.254	1.633
TN	0.752	0.599	0.654	1.254	1.150
TX	0.833	0.542	0.52	1.537	1.601
UT	0.703	0.710	0.518	0.990	1.356
VT	0.815	0.610	0.700	1.336	1.165
VA	0.885	0.671	0.837	1.319	1.058
WA	0.817	0.663	0.679	1.231	1.203
WV	0.643	0.290	0.614	2.216	1.048
WI	0.848	0.867	0.849	0.979	0.999
WY	0.620	0.230	0.468	2.699	1.323

Notes: Sample period: 1997-2017. $\hat{c}_i$, $\hat{y}_i$ and $\hat{pi}_i$ denote state-level log growth in consumption, output and personal income; $\hat{c}$, $\hat{y}$ and $\hat{pi}$ denote their aggregate counterparts.

the regional income growth. Compared to the traditional OLS approach, this framework is able to distinguish between regional and aggregate component of income shocks; in addition, it allows us to understand the regional income risk as well as consumption risk sharing together in a consistent way. The aim of this exercise is twofold. First, I estimate the time-varying regional risk, defined as the volatility of the regional shock to income; and study its business cycle properties. Second, I study the transmission of income shocks to consumption, indicating the extent of consumption risk sharing; and study its variation over the business cycle.

Income Process

I focus on the cyclical components of GDP and consumption by either looking at the growth rates or linearly detrended data. In particular, I assume that the income process of $\Delta \log y_{i,t}$, given by (1.1), has three components. First, there's a region-specific long run mean μ_i^y. This term captures the long-run heterogeneity that is independent of regional and aggregate business cycles. It could also capture the cross-sectionally heterogeneous exposures of regional income to aggregate shocks.

$$\Delta \log y_{i,t} = \mu_i^y + \chi_{i,t} + \Xi_t \tag{1.1}$$

Secondly, $\chi_{i,t}$, the primitive regional shock, follows an AR(1) process. This term is of utmost interest to us. It captures the idiosyncratic shock to regional income, and this heterogeneity is an key element throughout this study. Equation (1.2) denotes the process from which regional shocks are drawn. It's worth noting that I the volatility of the disturbance $e_{i,t}^{\chi}$, or the regional risk, is allowed to be time-varying. Later on, I will investigate in details the time variation in regional risk, especially its business cycle patterns.

$$\chi_{i,t} = \rho^{\chi}\chi_{i,t-1} + e_{i,t}^{\chi}, \quad e_{i,t}^{\chi} \sim i.i.d.N(0, \sigma_{\chi,t}^2) \tag{1.2}$$

Thirdly, persistent aggregate shocks are denoted by Ξ_t that also follow an AR(1) process in (1.3). It's common across regions, capturing the part of regional income that moves together with each other. Disturbances to the aggregate shock ε_t are i.i.d. across time.[6]

$$\Xi_t = \rho^{\Xi}\Xi_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim i.i.d.N(0, \sigma_{\Xi}^2) \tag{1.3}$$

Consumption Process

The key to understand regional risk sharing is to study the degree of transmission of income shocks to consumption. Intuitively, under complete asset market, regional shocks wouldn't matter for consumption as regions perfectly insure against each other on these idiosyncratic risks.

$$\Delta \log c_{i,t} = \mu_i^c + \varphi_t^{\chi}\chi_{i,t} + \varphi_t^{\Xi}\Xi_t + +u_{i,t}\mathbb{I}(t \leq 1997) + e_{i,t}^c, \quad e_{i,t}^c \sim i.i.d.N(0, \sigma_c^2) \tag{1.4}$$

Consumption follows the process specified in (1.4). A region-specific long run term is denoted by μ_i^c; the impacts of regional and aggregate income shocks on consumption are given by the loading factors φ_t^{χ} and φ_t^{Ξ} respectively, both of which are potentially time varying; $u_{i,t}$ captures the measurement error in consumption for years prior to 1997; $e_{i,t}^c$ represents innovations in consumption that are independent of those in income, say, preference shocks.

Understanding φ_t^{χ}

The time-varying income sensitivity of consumption to regional idiosyncratic income shock is denoted by φ_t^{χ}. Previous literature on household consumption insurance highlights the different degrees of consumption insurance against transitory or permanent shocks. Instead of estimating separately the impact of these two types of shocks, this paper simply assumes a persistent shock process. If the persistence parameter is closer to 1, this shock is harder to insure against by nature, absent complete market.

[6]Throughout the paper I use ε_t^x and $e_{i,t}^x$ to denote aggregate and regional i.i.d. disturbances respectively.

Under complete market, idiosyncratic income shocks don't matter for consumption, i.e. $\varphi_t^\chi = 0$. Without complete market, regional income shocks are partially smoothed through at least the following three channels. First, regions could smooth income shocks through *self insurance*. This may include households borrowing and saving, firms changing their investment etc. Second, regions could share risks through the goods *trade* network. When a region experiences a negative productivity shock, its terms of trade appreciates, partially offsetting the impact of this bad shock, a mechanism highlighted in Cole and Obstfeld (1991). Third, *government transfers* to regions experiencing negative shocks serves as an additional insurance mechanism promoting consumption insurance. The φ_t^χ parameter is unable to distinguish between these different channels, but rather provides an overall assessment of the degree of partial insurance, or consumption risk sharing. A smaller φ_t^χ indicates better risk sharing conditions; thus the extent of risk sharing is given by $1 - \varphi_t^\chi$.

Estimation

Although equations (1.1) and (1.4) look like standard OLS panel regression equations with time and region fixed effects, they can't be estimated using the standard method, because of the additional restrictions imposed through the processes of unobserved regional and aggregate shocks. Instead, this system of (1.1) (1.2)(1.3) and (1.4) is estimated jointly using the dynamic panel GMM estimation approach, following the literature dealing with household-level data pioneered by Blundell and Bond (1998), and applied extensively in e.g. Storesletten et al. (2004), Blundell et al. (2008), to name a few.

Assumption 1.1. *Initial conditions for regional and aggregate shocks* $\chi_{i,0} = \Xi_0 = 0$. *These shocks are uncorrelated* $\rho(\chi_{i,t}, \Xi_t) = 0, \forall i$.

These assumptions make it easy for us to derive moments of the estimation system. Initial condition of both shocks being 0 guarantees that the long-run means of both shocks are 0. Thus, the first-order (cross-time) moments in output and consumption growth implies that μ_i^y and μ_i^c are identified, i.e., $\mathbb{E}_i(\Delta \log y_{i,t}) = \mu_i^y$ and $\mathbb{E}_i(\Delta \log c_{i,t}) = \mu_i^c$. Subscript i represents cross-time moments and t for cross-sectional ones.

Apart from the long run mean differences, heterogeneity in regional income also comes from the idiosyncratic regional shocks. Thus, cross-sectional moments help identify parameters related to regional shocks. To make an intuitive argument on the estimation of each parameter, I start with an exactly identified system that directly relates each parameter to a data moment. Later on, I will discuss how the results are robust to adding more moment restrictions in an overidentified GMM estimation. I present next two sets of moments in a exactly identified estimation that identify the two key parameters of our interest, the risk sharing parameter ε_t^{χ} , and the regional risk $\sigma^2_{\chi,t}$. In Appendix A.3, I specify the moments used to identify other parameters in both the exactly and over-identified system.

First, by assuming that regional and aggregate shocks are uncorrelated, the time-varying risk sharing parameter φ_t^{χ} is derived combining consumption and income data moments

$$\varphi_t^{\chi} = \frac{Cov_t(\Delta \log y_{i,t}, \Delta \log c_{i,t}) - Cov(\mu_i^y, \mu_i^c)}{Var_t(\Delta \log y_{i,t}) - Var(\mu_i^y)} \tag{1.5}$$

The cross-sectional covariance of consumption and income is dictated by the degree of consumption response to regional income shocks, or the risk sharing parameter, as well as the variance of the regional income shocks. The latter is given by the denominator in Equation (1.5). Hence risk sharing parameter φ_t^{χ} could be estimated from (1.5).

Second, the conditional variance of the disturbance to regional shocks, $\sigma^2_{\chi,t}$, is given by

$$\sigma^2_{\chi,t} = Var_t(\Delta \log y_{i,t}) - Var(\mu_i^y) - (\rho^{\chi})^2 \left(Var_{t-1}(\Delta \log y_{i,t-1}) - Var(\mu_i^y)\right) \tag{1.6}$$

GMM Estimates

The GMM estimates of the two key parameters φ_t^{χ} and $\sigma_{\chi,t}$ are plotted in Figure 27. Estimates of the regional risk $\sigma_{\chi,t}$ were consistently around 0.02 during normal periods. However, a recession is always accompanied by a spike in regional risk. The surge in regional risk was more pronounced in the recessions in the 70s and 80s while in recent ones, even the most devastating one in decades, the regional risk went up but not as much in magnitude. The business cycle patterns for risk sharing parameter φ_t^{χ}, however, is less clear. On average, this parameter shows a significant time-variation pattern, how ever there's no clear pattern over the business cycle . For example, during the most recent recession, it rose from slightly below to above 0.2. And in previous ones, it either dropped or only rose slightly.

To confirm the visualized finding, I project the estimates of these two parameters on a dummy variable indicating NBER recessions, results presented in Table 2. The OLS coefficient on the dummy variable is not significantly different from 0 for the risk sharing parameter φ_t^{χ}, and significant for the regional risk estimates $\sigma_{\chi,t}$. The average estimate for the former is 0.26, implying that only around 26% of regional income shocks are not insured, and a large fraction of idiosyncratic income fluctuations has been smoothed away. Furthermore, the degree of risk sharing doesn't seem to be different in recession times, consistent with the message in the right panel of Figure 27. Estimate of regional risk $\sigma_{\chi,t}$, however, is found to be significantly larger during recessions than in normal times: the average estimate of regional risk in recessions is 0.0274, 40% larger than the estimate of the value 0.0197 for a normal time. These findings are also robust if we use linearly detrended data for consumption and income instead of growth rates in the GMM estimation, although the average estimate for φ_t^{χ} is larger.

The full estimation results of the GMM estimation are presented in Table 3. With the aforementioned business cycle results for the two time-varying parameters, the recession-insensitive risk sharing parameter φ_t^{χ} is condensed into a single parameter φ^{χ} (Column

Table 2: GMM Estimates Regressed on a Recession Dummy

	Growth		Detrended	
	φ_t^{χ}	$\sigma_{\chi,t}$	φ_t^{χ}	$\sigma_{\chi,t}$
Rec	0.082	0.008^{***}	-0.150	0.014^{***}
	(0.136)	(0.003)	(0.28)	(0.006)
Constant	0.234^{***}	0.020^{***}	0.401^{***}	0.022^{***}
	(0.070)	(0.001)	(0.034)	(0.003)
N	53	53	54	54

Notes: Standard errors are reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Columns 2-3 correspond to GMM estimates using growth rate data on consumption and output; Columns 4-5 correspond to GMM estimates using log linearly detrended data on consumption and output. Both are the estimates of an exactly identified system.

2), and the recession-sensitive regional risk parameter $\sigma_{\chi,t}$ is condensed into its average during recessions and normal times (Columns 3 and 4). Estimates of the time-fixed parameters φ^{Ξ} (sensitivity of consumption to aggregate income shock), σ_{Ξ} (volatility of noises to aggregate shock), ρ^{χ} (persistence of regional shock) and ρ^{Ξ} (persistence of aggregate shock) are presented in Columns 5-8.

The baseline results are reported in Row A using an exactly identified system and growth rates. Row B presents the estimation results within an overidentified system (details in Appendix A.3). Rows C and D replicate A and B, but using log-linearly detrended data. Table 3 conveys three key messages. First, the differences between exactly identified and overidentified results are minimal in all the parameter estimates. This provides extra validity for the identification strategy described above: it's the equations that are used in the exactly identified system that are key to the identification; additional restrictions do not matter too much. Second, using detrended data or growth rates matters for the regional risk, risk sharing and two persistence parameter estimates. Risk sharing parameter estimated from the detrended data is larger than that from growth data. And the volatilities of both regional and aggregate shocks implied by the former are estimated to be larger. However, as noted above, business cycle patterns

Table 3: GMM Parameter Estimates

	φ^{χ}	σ_{χ} (recession)	σ_{χ} (normal)	φ^{Ξ}	σ_{Ξ}	ρ^{χ}	ρ^{Ξ}
A. EI, Growth	0.26	0.0274	0.0197	0.670	0.021	0.240	0.255
	(0.034)	(0.007)	(0.004)	(0.083)	(0.005)	(0.045)	(0.078)
B. OI, Growth	0.23	0.0253	0.0188	0.720	0.024	0.292	0.343
	(0.023)	(0.005)	(0.003)	(0.057)	(0.004)	(0.044)	(0.080)
C. EI, Detrended	0.36	0.0358	0.022	0.688	0.021	0.906	0.925
	(0.064)	(0.005)	(0.006)	(0.095)	(0.007)	(0.191)	(0.136)
D. OI, Detrended	0.35	0.033	0.024	0.70	0.022	0.892	0.911
	(0.056)	(0.004)	(0.008)	(0.122)	(0.006)	(0.125)	(0.185)

Notes: "EI" and "OI" are short for "exactly identified" and "over identified" respectively. Standard errors are reported in parentheses; they are computed using the White (1980) estimator. Rows A and C report the estimates from the exactly identified system; Rows B and D report the estimates from the over-identified system. In A and B, the inputs are growth rate data on consumption and output; while in C and D, log linearly detrended data are used.

are the same between these two sets of estimates. When it comes to shock persistence, the estimates are remarkably different. This is because of the difference between auto-correlations of aggregate GDP growth (around 0.3) and detrended GDP (0.89) in the data. It's not key to the empirical analysis so far, but it will matter for the calibration exercise in the quantitative part, where I use Row C to discipline the model parameters in the business cycle model where growth is not modeled. Third, the sensitivity of consumption to a regional shock is much lower than to an aggregate one. It accords with the idea that idiosyncratic shocks are easier to insure against than aggregate shocks.

Overall, my GMM estimation provides robust evidence for countercyclical regional risk, and acyclical risk sharing: the regional income shocks are 40% more volatile in recessions than in normal times, while the degree of risk sharing has been insensitive to business cycle fluctuations and on average 70% − 80% regional income shocks are insured, suggesting sizable risk sharing across regions.

1.3.4 OLS Results

The GMM estimation approach has its advantage of jointly estimating regional risk and risk sharing. It's nonetheless worth testing these results in a classic estimation framework, in which risk sharing is measured by regressing consumption growth rates on idiosyncratic income growth, usually written as the regional income growth relative to the aggregate. The benchmark regression is specified in Equation (1.7). β_1, the sensitivity of consumption growth to regional income growth, is interpreted as the risk sharing coefficient. Different from traditional estimations, I include a interaction term which is the product of relative regional income growth and a recession dummy variable, as a separate independent variable. The coefficient on this term β_1^{rec} is interpreted as the difference of risk sharing between recession and normal times. ν_i stands for the region fixed effect, and $u_{i,t}$ denotes the measurement error, which is orthogonal to $\epsilon_{i,t}$, denoting the innovations to consumption that are independent of those in income.

$$\begin{aligned}\Delta \log c_{i,t} - \Delta \log c_t =& \beta_0 + \beta_1(\Delta \log y_{i,t} - \Delta \log y_t) + \beta_1^{rec} \left[(\Delta \log y_{i,t} - \Delta \log y_t) \times \mathbb{I}(recession)\right] \\ &+ \nu_i + u_{i,t}\mathbb{I}(t \leq 1997) + \epsilon_{i,t}\end{aligned} \tag{1.7}$$

Estimations results for the benchmark equation is reported in Column 4 of Table 4 when I use GDP as the income measure, and Column 7 when using personal income. β_1^{rec} is estimated to be insignificant, confirming our previous results on acyclical risk sharing. The pass-through parameter β_1 is consistently estimated to be between (very close to) 0.2 and 0.3, depending on how income is measured, whether an interaction term is included, and whether region fixed effects are allowed for. I find that in general, the β_1 is estimated to be higher when personal income growth is included as the independent variable, compared to GDP. The difference likely comes from the fact that personal income includes transfer receipts from the federal government, so personal income is to some extent smoothed from GDP. This jibes with the second picture in Figure 2, where dispersion of personal income growth is often lower than that of GDP especially

Table 4: Regional Risk Sharing: OLS Estimation Results

	$y = GDP$			$y = PersonalIncome$		
	A	B	C	A	B	C
$\Delta \log GDP$	0.194***	0.195***	0.207***			
	(0.039)	(0.039)	(0.046)			
$\Delta \log GDP \times Rec$			-0.035			
			(0.081)			
$\Delta \log PI$				0.249***	0.259***	0.284***
				(0.070)	(0.071)	(0.070)
$\Delta \log PI \times Rec$						-0.098
						(0.062)
Constant	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	2544	2544	2544	2688	2688	2688

Notes: Clustered robust standard errors are reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Specification "A" does not include an interaction term; specification "B" does not have fixed effects; specification "C" is the benchmark in 1.7. Sample size is 48 states, leaving Alaska, DC, and Hawaii out. Columns 2-4 show the results of risk sharing OLS regressions using regional GDP as the independent variable. Columns 5-7 show the results using regional personal income as the independent variable.

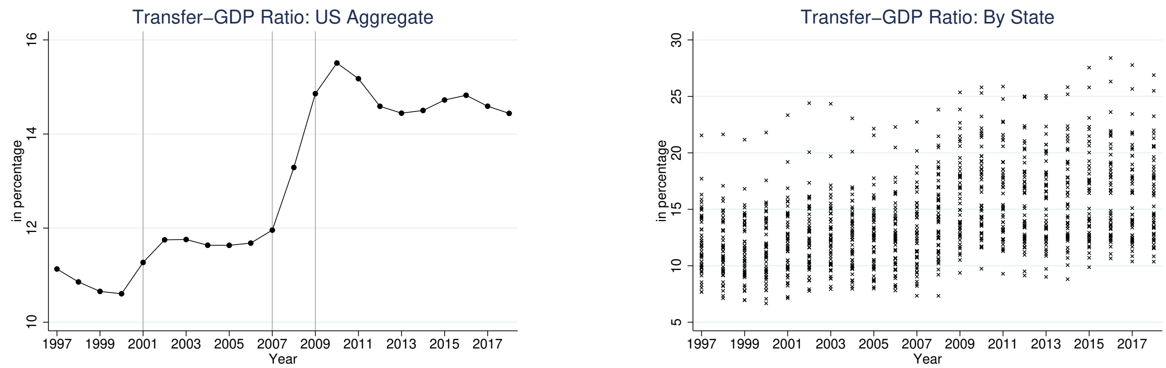
in recession years.

1.3.5 Federal Government Net Transfers

Scale of Federal Government Transfers

Figure 3 displays federal fiscal transfer-GDP ratios for US aggregates (left) and by-state (right). In the data sample, the aggregate transfer-GDP ratio has been always above 10%, indicating an economically significant role of federal transfers in the US economy as a whole. When one focuses on the business cycle pattern of this ratio, there seems to be a clear countercyclical pattern: going into a recession, the 2001 one or the Great Recession, total federal transfer as a fraction of GDP has risen substantially, compared

Figure 3: Federal Government Transfers as a Fraction of GDP



Notes: Left: aggregate federal government transfer receipts as a fraction of US GDP; Right: state-level federal government transfer receipts as a fraction of state GDP, excluding Alaska, DC, and Hawaii.

with the stable or even declining pattern for years leading to these recessions. The right-hand-side picture shows that there's substantial variation in the state-level ratios, ranging from less than 10% to greater than 25%. Next, I show how these variations across states are related to the state-level economic performances.

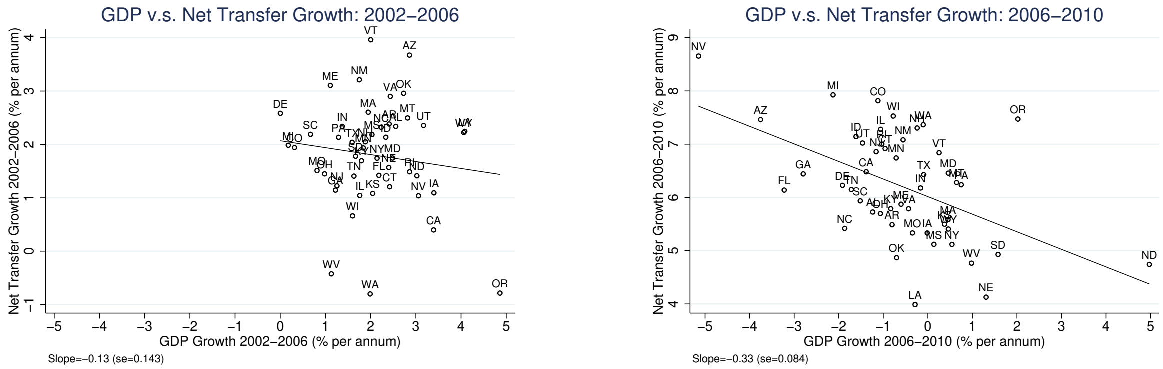
A "State-Contingent" Pattern

The feature of federal government net transfers, transfer net of tax, provides insights on why risk sharing hasn't become worse during recessions. The risk sharing role of an integrated fiscal system has been studied in Sala-i Martin and Sachs (1991), Asdrubali et al. (1996) and more recently Farhi and Werning (2017) and Beraja (2019). However, do the fiscal transfers work in the same way between normal and recession times? The state-level data inform us that the answer is no. I plot the GDP v.s. net transfer growth by state for pre-recession years 2002-2006 and recession years 2006-2010 in Figure 4, and find that the cross-sectional correlation between GDP and net transfer growth for normal time is not significantly different from 0, while for recession years it is significantly negative. I call this negative correlation during recession times the "state-contingency" in the federal fiscal transfer policy: regions that experience the most negative shock, thus hit worst by the recession, receive the best fiscal support from the federal government, and vice versa.

A formal test of this finding is conducted using both OLS and and IV estimation approaches, and the results are presented in Table 5. For OLS estimation, I simply regress regional net transfer growth on regional GDP growth respectively for the two periods. I find that the coefficient is –0.33 and significantly different from 0 for the recession period, while insignificant for the pre-recession normal times. To account for the potential endogeneity problem, I use state-level housing price growth as an instrument. This is motivated by the empirical evidence provided by Mian and Sufi (2014), who argue that house price growth strongly predicts regional income growth. And this instrument is valid under condition that the regional house price level is uncorrelated with the federal fiscal transfer policy, and the only way they are related is through the former's impact on the strength of regional economy. Columns 4-5 present the estimation results of the second stage of the two-state least squares estimation. First, our previous conclusion on "state-contingent" transfer policy during recession periods remains valid: the coefficient on GDP growth is significantly negative for the 2006-2010 sample, and insignificant when we use the 2002-2006 sample. Second, the magnitude of estimated fiscal transfer response to regional GDP growth shock is almost twice as large as that coming from OLS, suggesting even stronger pattern for "state contingency".

What accounts for this special feature of federal net transfer in the U.S.? I first confirm that it is the gross transfer that drives this pattern, rather than tax. In fact, Table 13 shows that when I decompose the net transfer into gross transfer and tax, and redo the exercise in Table 5 with these two parts separately, the estimation results using total transfers closely track the net results. In particular, total transfers are larger in economically weaker regions during the recession, and there's no significant difference across states in transfers in pre-recession years. However, tax payments are "state-contingent" in both periods, which is self explanatory. Taken together, it's the total transfers that dominate in understanding the observed business cycle patterns of net fiscal transfers.

Figure 4: Federal Government Net Transfer Growth v.s. GDP Growth



Notes: x-axis: annualized percentage growth rates of state-level GDP; y-axis: annualized percentage growth rates of net transfers (gross transfer minus tax) at the state level. OLS fitted lines are added.

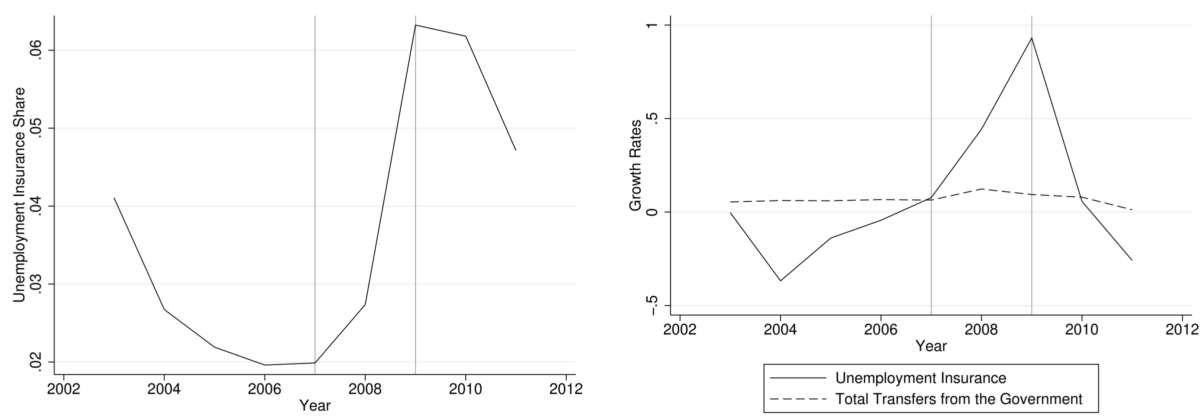
I next further investigate the total transfer by its subcategories: retirement and disability insurance benefits, medical benefits, income maintenance benefits, unemployment insurance compensation, veterans' benefits, education and training assistance, and other transfer receipts of individuals from governments. Among all these components, only unemployment insurance fluctuates dramatically over the business cycle. First, the share of transfers that go to unemployment insurance was tripled during the Great Recession. Second, growth rates of unemployment insurance transfers went from very negative in pre-recession years to very positive during the recession, while other forms of transfer went almost stable. These two observations suggest that unemployment insurance has played a much bigger role in the total transfers during the recession. In addition, unlike other transfers, unemployment insurance is state-contingent by its nature: regions hit the most during the recession are eligible for more unemployment benefits as these regions typically had relatively higher unemployment rates. To put it differently, unemployment insurance can be regarded as an economically-targeted transfer, a characteristic not shared with other types of transfers. Combining this observation with the fact that unemployment played a surging role during the recessions makes it easy for us to understand why the federal fiscal transfer policy is state-contingent during recessions, but not normal times.

Table 5: Net Fiscal Transfer before and during the Great Recession

	OLS		IV	
	Net Transfer Growth (06-10)	(02-06)	(06-10)	(02-06)
GDP Growth (06-10)	-0.330***		-0.624***	
	(0.082)		(0.145)	
GDP Growth (02-06)		-0.130		-0.104
		(0.169)		(0.394)
Constant	6.016***	2.069***	5.845***	2.016***
	(0.145)	(0.343)	(0.172)	(0.767)
N	48	48	48	48

Notes: Robust standard errors are reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sample size is 48 states, leaving Alaska, DC, and Hawaii out.

Figure 5: Unemployment Insurance



Notes: left panel shows the share of unemployment insurance in the total transfer receipts of individuals from the federal government; the right panel depicts the annual growth rates of unemployment insurance and that of total transfers. Grey lines stand for the start and end of the Great Recession.

1.3.6 Taking Stock

In this section, I've presented extensive empirical evidence supporting the following three main results and find them to be robust to alternative estimation specifications: 1). regional risk is strongly countercyclical; 2). the degree of regional risk sharing is no different in recessions than in normal times; 3). federal fiscal transfer policy is state-contingent during recessions but not in normal times.

In the following sections, I incorporate the data features 1) and 3) into a quantitative model to show how they matter for understanding 2). In addition, I'll show how these novel considerations are relevant to aggregate fluctuations during a recession.

1.4 Model

I develop a New Keynesian monetary union model that features: a continuum of measure 1 regions denoted by $i \in [0, 1]$ that trade intermediate goods with each other; incomplete asset market where households may only trade nominal bonds and are subject to a credit constraint; federal government fiscal transfers that are contingent on regional economic performances; and a monetary authority that sets a union-wide nominal interest rate. In this section, I describe the model in detail, define an equilibrium, and discuss the key model features in a qualitative manner.

1.4.1 Regional Firms

Final Good Producer

Non-tradeable final good $X_{i,t}$ producers are perfectly competitive, and they solve the following profit maximization problem

$$\max_{y^j_{i,t}} \left\{ P_{i,t} X_{i,t} - \int_0^1 p^j_{i,t} y^j_{i,t} dj \right\}$$

subject to the final good production function

$$X_{i,t} = \left[\int_0^1 \left(y_{i,t}^j \right)^{\frac{\eta-1}{\eta}} dj \right]^{\frac{\eta}{\eta-1}}$$

where η is the elasticity between goods produced in different regions. $y_{i,t}^j$ and $p_{i,t}^j$ denote quantity and price of intermediate goods produced in region j that are sold in region i. Note here that I have assumed away home bias, so this setting captures an economy with very open regional interactions. We further assume that the trade cost is zero [7], so $p_{i,t}^j = p_t^j$. The demand of region i for intermediate goods produced in region j is

$$y_{i,t}^j = \left(\frac{p_t^j}{P_{i,t}} \right)^{-\eta} X_{i,t} \tag{1.8}$$

where consumer prices in region i is given by

$$P_{i,t} = \left[\int_0^1 \left(p_t^j \right)^{1-\eta} dj \right]^{\frac{1}{1-\eta}} \tag{1.9}$$

Intermediate Good Producer

Intermediate goods are traded across regions, as bundles of variety goods, and they are used to produce the regional final good. In addition, they are themselves CES composites of varieties of differentiated inputs indexed by k, with an elasticity of substitution θ between these varieties.

$$y_t^i = \left[\int_0^1 \left(y_t^i(k) \right)^{\frac{\theta-1}{\theta}} dk \right]^{\frac{\theta}{\theta-1}}$$

It follows that demand for an individual variety k is

$$y_t^i(k) = \left(\frac{p_t^i(k)}{p_t^i} \right)^{-\theta} y_t^i \tag{1.10}$$

where the region i producer price p_t^i is

$$p_t^i = \left[\int_0^1 p_t^i(k)^{1-\theta} dk \right]^{\frac{1}{1-\theta}} \tag{1.11}$$

[7] When there is trade cost, spot prices of goods produced in region j differ by the destination regions, the degree to which depends on the dispersion of origin-destination-specific iceberg trade costs.

Variety Good Producer

The production function of variety goods is linear in labor, and subject to a stochastic region-specific productivity $A_{i,t}$

$$y_t^i(k) = A_{i,t} n_{i,t}(k)$$

Nominal marginal costs are the same for all varieties within the same region: $MC_{i,t}(k) = MC_{i,t} = W_{i,t}/A_{i,t}$. The specifics of nominal rigidity in output price is not important here (Rotemberg v.s. Calvo). I follow the standard New Keynesian models and assume the variety producers are subject to a Calvo-style friction. In particular, a fraction $1-\xi$ of these firms can re-optimize their price each period, while the rest ξ cannot. Firms are owned by regional households, so they discount their future profits using the regional household's pricing kernel $\Lambda_{i,t+s}$ (to be defined in the household problem). For a firm that could adjust its price at time t, its profit maximization problem is

$$\max_{p_t^i(k),\{y_{t+s}^i(k)\}_{s=0}^{\infty}} \mathbb{E}_t \left\{ \sum_{s=0}^{\infty} (\beta\xi)^s \Lambda_{i,t+s} y_{t+s}^i(k) \left(p_t^i(k) - MC_{i,t+s}(k)\right) \right\}$$
$$\text{s.t.} \quad y_{t+s}^i(k) = \left(\frac{p_t^i(k)}{p_{t+s}^i}\right)^{-\theta} y_{t+s}^i$$

For the firms that reset prices, their optimal prices are equal

$$p_t^{i*} = p_t^{i*}(k) = \frac{\theta}{\theta-1} \frac{\mathbb{E}_t \sum_{s=0}^{\infty} (\beta\xi)^s u'(C_{i,t+s}) MC_{i,t+s} \left(p_{t+s}^i\right)^{\theta-1} y_{t+s}^i}{\mathbb{E}_t \sum_{s=0}^{\infty} (\beta\xi)^s u'(C_{i,t+s}) \left(p_{t+s}^i\right)^{\theta-1} y_{t+s}^i} \tag{1.12}$$

Regional producer price evolves according to

$$p_t^i = \left[(1-\xi)\left(p_t^{i*}\right)^{1-\theta} + \xi\left(p_{t-1}^i\right)^{1-\theta}\right]^{\frac{1}{1-\theta}} \tag{1.13}$$

1.4.2 Regional Households

Each region is populated by a representative household. Members of this household cannot move across regions. Each period, these households make consumption, saving and labor supply decisions, taking prices as given. We assume that wages are flexible. The period utility is given by

$$u(C, N) = \frac{C^{1-\gamma}}{1-\gamma} - \psi \frac{N^{1+\nu}}{1+\nu}$$

where C denotes consumption and N for hours worked; γ is the constant relative risk aversion parameter, ν is the Frisch elasticity of labor supply, and ψ measures the relative willingness to work. Regional household's problem is

$$\max_{C_{i,t}, N_{i,t}, B_{i,t}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(C_{i,t}, N_{i,t}) \tag{1.14}$$

$$\text{s.t.} \quad P_{i,t}C_{i,t} + B_{i,t} = R_{t-1}B_{i,t-1} + W_{i,t}N_{i,t} + T_{i,t} + \Pi_{i,t} \quad \text{(Budget Constraint)} \tag{1.15}$$

$$B_{i,t} \geq -b \quad \text{(Credit Constraint)} \tag{1.16}$$

$\Pi_{i,t}$ is the profit earned by regional intermediate firms and is distributed as dividends to the regional households; $T_{i,t}$ the net federal government transfers, following a fiscal rule to be specified in 1.4.4; b is the credit constraint, common to all the regions. The pricing kernel for region i is then defined as $\Lambda_{i,t+s} = (C_{i,t+s}/C_{i,t})^{-\gamma}$.

1.4.3 Aggregate Variables

Before moving on to the government problems, it's useful to define aggregate variables in this model that are usually what the policy makers target. Aggregate output $Y_t = \int_0^1 y_t^i di$; aggregate consumption $C_t = \int_0^1 C_{i,t} di$; aggregate labor $N_t = \int_0^1 N_{i,t} di$. It follows from the assumptions of no home bias and no trade cost that consumer prices are equalized across regions, see Equation (1.9). Thus the aggregate consumer price P_t is equal to its regional counterparts given by Equation (1.9). This is of course counterfactual, but it greatly simplifies the model solution given that the computation burden is already very high. Aggregate CPI inflation $\pi_t = \log(P_t/P_{t-1})$.

1.4.4 Policy Makers

In this model, I deliberately place no role for state governments to focus exclusively on how federal government policies, that is, federal fiscal and monetary policies, may help stabilize the regional and aggregate economy. To make the two roles transparent and for the sake of simplicity, I also ignore the role of federal government spending.

Federal Fiscal Policy

The federal government issues debt and transfers resources across regions, subject to the budget constraint

$$B_t = R_{t-1}B_{t-1} + T_t \tag{1.17}$$

where $B_t = \int_0^1 B_{i,t}di$ is the government debt issuance (liability), and $T_t = \int_0^1 T_{i,t}di$ is the federal government total net transfers. I assume, similar to Beraja (2019), that the federal government tax-and-transfer in each region follows a policy rule, which can be summarized as federal lump-sum transfers that are functions of regional economic variables. In particular, federal government (net) transfer policy follows a state-contingent rule:

$$T_{i,t} = \bar{T}{y_{i,t}}^{\vartheta_y} \tag{1.18}$$

In Section 1.5.2 provides more details on the estimation of parameters in this rule.

Monetary Policy

Monetary policy targets aggregate inflation and is assumed to follow a Taylor rule of the form

$$\frac{R_t}{R} = \left(\frac{P_t}{P_{t-1}}\right)^{\phi_\pi} \tag{1.19}$$

where I assume no unexpected monetary shocks. Output gap is omitted because, as pointed out in McKay and Reis (2016), a constrained-welfare natural level of output to which policy should respond is not well-defined with incomplete markets.

1.4.5 Market Clearing

Absent investment and local government spending, the regional final good market clear implies that

$$X_{i,t} = C_{i,t} \tag{1.20}$$

Market clears for the tradeable intermediate good

$$y_t^i = \int_0^1 y_{j,t}^i dj \tag{1.21}$$

Labor market clears

$$\int_0^1 N_{i,t}(k)dk = N_{i,t} \tag{1.22}$$

Bond market clears

$$B_t = \int_0^1 B_{i,t} di \tag{1.23}$$

And finally, regional resource constraint (in nominal terms) follows

$$\underbrace{p_t^i y_t^i - P_{i,t}X_{i,t}}_{\text{Net Export}} + T_{i,t} = \underbrace{B_{i,t} - R_{t-1}B_{i,t-1}}_{\text{Current Account}} \tag{1.24}$$

1.4.6 Shocks

First, $A_{i,t}$, the exogenous regional productivity, has an aggregate component a_t and regional component $z_{i,t}$, both of which follow AR(1) processes

$$\begin{aligned}\log A_{i,t} &= a_t + z_{i,t} \\ a_t &= \rho_a a_{t-1} + \varepsilon_t^a, \quad \varepsilon_t^a \sim i.i.d.N(0, \sigma_a^2) \\ z_{i,t} &= \rho_z z_{i,t-1} + e_{i,t}^z \quad e_{i,t}^z \sim i.i.d.N(0, \sigma_{z,t}^2)\end{aligned} \tag{1.25}$$

ε_t^a is a Gaussian disturbance that is identically and independently distributed across time; $e_{i,t}^z$ is identically and independently distributed across regions but not across time. Time-varying regional risk is captured by $\sigma_{z,t} = (\sigma_z^H, \sigma_z^L)$, that follows a two-state Markov chain with state-transition matrix

$$\Pi = \begin{bmatrix} 1-\pi_{HL} & \pi_{HL} \\ \pi_{LH} & 1-\pi_{LH} \end{bmatrix} \tag{1.26}$$

Top sum up, the economy is potentially driven by both supply shocks (a_t, $z_{i,t}$) and demand shocks ($\sigma_{z,t}$). It would be straightforward to add more shocks to this model economy, for example, monetary policy shocks, credit shocks (e.g. Jones et al. (2018), Guerrieri and Lorenzoni (2017)), preference shocks (e.g. Beraja et al. (2019)), markup shocks (e.g. McKay and Reis (2016)) or investment-specific technology shocks in a model with capital accumulation, all of which I abstract to 1) get across a clear role of time-varying regional risk, fiscal policy and monetary policy in driving regional risk sharing and aggregate fluctuations; and 2) reduce the computation burden.

1.4.7 Equilibrium

Equilibrium Definition

An equilibrium in this economy is a collection of aggregate quantities (Y_t, C_t, N_t); aggregate prices (P_t, π_t); regional quantities $(y_t^i, y_{i,t}^j, C_{i,t}, N_{i,t}, B_{i,t})$; regional prices $(p_t^i, p_t^{i*}, P_{i,t}, W_{i,t})$; government policies $(R_t, B_t, T_{i,t})$; and a distribution of regions over regional shocks and assets $\mu(z, B)$ such that:

1. regional households optimize (1.14) subject to budget constraint (1.15) and credit constraint (1.16), taking prices and distributions as given.

2. the distribution μ over household assets B and idiosyncratic shocks z evolves in a manner consistent with household decision rules and shock processes (1.25).

3. final good producers behave optimally according to (1.8) and (1.9); intermediate good producers behave optimally according to (1.10) and (1.11); variety good producers set optimal prices following (1.12) and the regional producer price follows (1.13).

4. monetary and fiscal policies follow the rules specified in (1.19) and (1.18), and the federal government is subject to a budget constraint (1.17).

5. market clears for the regional final good as in (1.20), tradeable intermediate good as in (1.21), regional labor market as in (1.22), and government bond market as in (1.23).

State Variables

I solve the model recursively by computing a fully global approximation of individual region's behaviors, so it's useful to make explicit here the state variables. There are two idiosyncratic state $s_i = (z_i, B_i)$, and four aggregate state $\mathcal{S} = (a, \sigma_z, \mu)$, where μ is the distribution over (z, B)-pairs. In Appendix A.4, I reformulate the household and firm optimization problems in a recursive way, and lay out all the equilibrium equations in solving the model.

1.5 Quantitative Analysis

In this section, I outline the solution method of estimating the model, discuss the estimation strategy of model parameters, repeat the empirical exercise as in Section **??** with a sample simulated from the model, investigate the mechanisms underlying the empirical facts, and study the quantitative implications of each channel with some counterfactual exercise focusing on the recent Great Recession.

1.5.1 Solution Method

I use the solution algorithm developed by Winberry (2018), which is built on Reiter (2009). The latter approximates the distribution with a fine histogram, while the former does this with a flexible parametric family, which reduces its dimensionality to a finite set of endogenous parameters. The method of Winberry (2018) involves three main steps. First, all the equilibrium objects are approximated using finite-dimensional objects that approximate the infinite-dimensional distributions. This step is key to this method. Second, a stationary equilibrium of the approximated model is computed, where all the aggregate shocks are absent but idiosyncratic shocks still exist. Third, the aggregate dynamics of the approximated model could be approximated around its stationary equilibrium using the standard perturbation method. The combination of global approach in the first step and the local approach in the third step makes the system solved more quickly than the Reiter (2009) method. Details on the recursive formulation and exact solution algorithm are relegated to Appendix A.4.

1.5.2 Parameterization

The model is estimated in quarterly frequency. There are 18 parameters to be calibrated or estimated in this model, of which 12 are externally calibrated by either taking from the literature for those standard ones, or matching some data moments. The other 6 are internally calibrated using simulated method of moments (SMM).

Risk aversion parameter γ is set equal to 2, which is commonly used in the macro literature. Coefficient on labor disutility ψ is calibrated to be 12.5 to match the average hours worked in Nekarda and Ramey (2011). I follow a large number of literature and assume the curvature on labor disutility ν to be 2, so that the Frisch elasticity is equal to 1/2. Discount factor β is calibrated to match the 2.5% real interest rate. The estimate of regional trade elasticity η is controversial in the literature, and here I pick 0.5, which is at the lower bound of the estimates in the literature. In the sensitivity analysis in Section 7, I'll experiment with the trade elasticity parameter to see how our results are sensitive to this parameter choice. Substitution between varieties θ is set to be 10 following the calibration in House et al. (2018) who have a similar production structure to mine. I follow the estimates by Beraja et al. (2019) in setting the Calvo price stickiness parameter ξ. The value indicates that it takes on average three quarters to adjust variety goods prices. In the baseline exercise, I use a transfer parameter of –0.33 that corresponds to the OLS estimation results. In the sensitivity analysis, I'll change this parameter to –0.624, the IV regression estimate, to see how it drives the results. The fixed parameter in the transfer rule $\bar{T}$ is set to be 0.1, to match the average transfer to GDP ratio around the Great Recession years. Taylor rule coefficient is set equal to 1.5, and it will also be experimented with larger or smaller values. I calibrate the Markov transition probabilities between high and low regional risk regimes so that they match the historical frequency of recessions and normal times, as in my model recessions are alway accompanied with higher regional risk and vice versa. To practically apply the solution algorithm which requires local approximation in the third step, I convert the Markov-switching process of regional risk into a continuous AR(1) process. Nonetheless, for exposition purposes, it's easier to present the method in terms of a "high risk, low risk" statement.

Other parameters are new to the literature, requiring a formal estimation procedure. In particular, the borrowing limit b, persistence of aggregate and idiosyncratic productivity shocks ρ_a and ρ_z, standard deviation of aggregate productivity innovations σ_a, standard deviation of regional productivity innovations σ_z^H and σ_z^L are key to the quantitative exercise, and they are jointly estimated using SMM in which the SMM estimator minimizes the sum of squared percentage deviations from the model and data moments. In particular, I target the first moment of the idiosyncratic shock to income and the aggregate shock to income. Because the model distinguishes between the regional and aggregate shock, it could generate the regional and aggregate components of regional income (GDP). Therefore, I also target the empirical estimates (using an exactly identified approach with detrended data) of: 1. persistence of the aggregate shock to income; 2. persistence of the idiosyncratic shock to income; 3. the standard deviation of the aggregate shock to income; 4. the standard deviations of the idiosyncratic shock to income in low and high regimes. In addition, the borrowing limit is closely related to the ergodic wealth distribution, so I also target the first and second moments of the state-level household debt distribution data retrieved from the Federal Reserve Bank of New York.

Different from the conventional calibration exercise in which those models are assumed to match the entire data sequence, the parameters in this model are calibrated in two separate models: one with a "state-contingent" fiscal transfer rule for a recession regime and one without for a normal regime. This consideration is motivated by the empirical evidence and serves as a key distinction between the recessions and normal times, which matters for the stationary distribution and the aggregate dynamics thereafter. In particular, $b, \rho_a, \rho_z, \sigma_a$ and the average regional risk σ_z are calibrated in a model where there's no regional risk shock, and I find these estimates are insensitive to how transfer rules are specified. σ_z^H is calibrated in a model with a state-contingent transfer rule to match the standard deviation of idiosyncratic shock to income in recessions, whereas σ_z^L is calibrated in a model without a state-contingent transfer rule to match the standard deviation of idiosyncratic shock to income in recessions. Table 6 summarizes all the calibrated and estimated parameters. The model-generated moments broadly match the data moments specified above.

1.5.3 Stationary Equilibrium

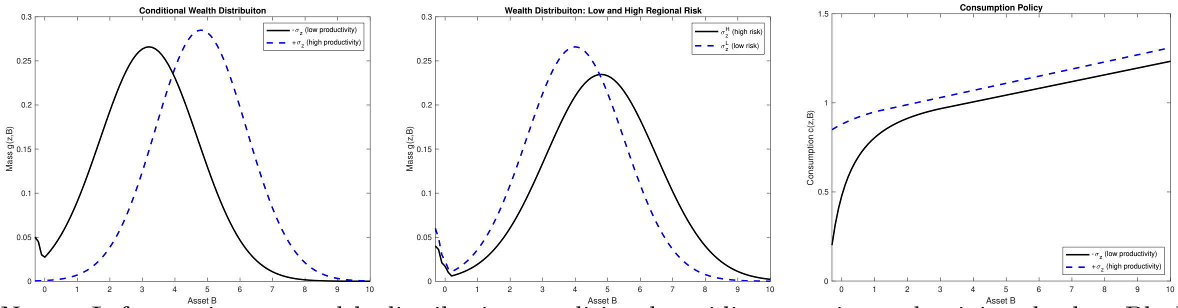
A stationary equilibrium of this model is the equilibrium where there's idiosyncratic shocks but no aggregate ones. In particular, conditional on the zero aggregate productivity shock and regional risk at the level σ_z, stationary distribution could be written as $\mu^*(z, B)$ and stationary policy function is denoted as $c^*(z, B)$. Figure 6 plots the distributions at the stationary equilibrium as well as the policy functions.

The left panel depicts the wealth distribution conditional on the regional productivity shock. Households hit by the negative productivity shocks on average hold fewer assets than those hit by positive ones. Moreover, a larger fraction of the former were borrowing constrained. This is easy to understand: conditional on the aggregate shock, regions receiving negative shocks are hit harder, and they have stronger incentive to borrow to smooth consumption, therefore the probability of being at the borrowing constraint is

Table 6: Parameter Calibration

Parameters	**Meaning**	**Baseline**	**Target**
		Externally Calibrated Parameters	
γ	risk aversion	2	Standard
ψ	coefficient on labor disutility	12.5	Avg. hours worked (Nekarda and Ramey, 2011)
ν	curvature on labor disutility	2	Frisch Elasticity=1/2
β	discount factor	0.976	Real interest rate=2.5%
η	trade elasticity	0.5	
θ	substitution between varieties	10	House et al. (2018)
ξ	Calvo price stickiness	0.67	Beraja et al. (2019)
ϑ_y	Transfer rule coefficient	–0.33	Estimated
$\bar{T}$	Transfer rule constant	0.1	Avg. transfer to GDP ratio
ϕ_π	Taylor coefficient	1.5	
π_{HL}	bust to boom p.	0.074	NBER Business Cycle
π_{LH}	boom to bust p.	0.023	NBER Business Cycle
		Internally Calibrated Parameters	
b	borrowing limit	0.3	1st and 2nd moments of debt distribution
ρ_a	AR(1) coefficient of agg productivity	0.93	Persistence of agg. shock to income
ρ_z	AR(1) coefficient of idio. productivity	0.90	Persistence of idio. shock to income
σ_a	s.t.d. of agg. productivity	0.021	s.t.d. of agg. shock to income
σ_z^H	s.t.d. of idio. productivity in bust	0.043	s.t.d. of idio. shock to income in bust
σ_z^L	s.t.d. of idio. productivity in boom	0.027	s.t.d. of idio. shock to income in boom

Figure 6: Stationary Equilibrium Results



Notes: Left: stationary wealth distribution conditional on idiosyncratic productivity shocks. Black solid line plots the probability mass function of bond holdings B, for regions that receive a positive one standard deviation regional productivity shock; blue dashed line plots that for regions that receive a negative one standard deviation shock. Center: stationary wealth distribution for different levels of regional risk. Black solid line plots the wealth distribution when regional risk is high, at σ_z^H; and the blue dashed line plots a low risk regime. Right: consumption policy function at the stationary equilibrium conditional on idiosyncratic productivity shocks. Similar to that of the conditional wealth distribution, black solid line corresponds to a negative shock and the blue dashed line to a positive shock.

higher.

The center panel plots the stationary wealth distribution by varying the steady state regional risk level, conditional on zero regional productivity shocks. Households on average accumulate more asset if the regional risk is higher (black solid line). This is explained by the precautionary motive of households facing higher idiosyncratic income risk, similar to the idea stressed in McKay (2017) and Ravn and Sterk (2017) where they study the interaction of time-varying precautionary saving stemming from time variation in labor income risk, and aggregate demand fluctuations.

Consumption policy functions are shown in the right panel. MPC out of wealth tends to decline in wealth: consumption for households with little wealth responds much more to income/wealth changes than the wealth-abundant ones. This feature tends to hold also on the income dimension: conditional on asset level, MPC is higher if a household is hit with a negative shock than a positive one, especially at the lower end of the wealth distribution. For wealth-abundant households, MPC do not seem to vary with either wealth or the idiosyncratic shock they receive.

Taken together, the stationary equilibrium provides three key insights as follows: 1.

regions receiving bad productivity shocks tend to accumulate less assets, and are more likely to be constrained by the borrowing limit; 2. higher regional risk is associated with more asset accumulation (saving); 3. MPC is higher for low wealth and low productivity regions.

1.5.4 Impulse Responses

Before conducting the counterfactual analysis, it's useful to investigate how the regional economies respond to various shocks under different episodes. In particular, the main concern here is how increased regional risk together with the fiscal transfer policies shape the regional risk sharing pattern during an economic downturn.

In the model economy, three shocks are taking place at the same time: regional productivity, aggregate productivity, and regional risk. In the simulation of the economy, I mimic a recession period as the combination of a negative aggregate productivity shock and a positive shock to regional risk, reaching the level of σ_z^H. Essentially, we can separately study two episodes in our impulse response exercise. First, consumption response to the regional productivity shock in both a recession regime and a expansion regime. This corresponds to our empirical exercise on the consumption sensitivity to regional income shocks. Second, consumption dispersion response to a negative aggregate productivity shock and compare the differences between a high risk regime and a low one. In the model economy, an alternative measure of the degree of regional risk sharing is the dispersion of consumption, as shown in the empirical section. Therefore, by comparing the response of $\sigma_t(c_i)$ to an aggregate shock across different scenarios, in particular, high vs. low regional risk, and an economy with vs. without state-contingent transfer rule, we could have a better idea of how risk sharing is determined by each factor in isolation.

Regional Productivity Shock

Consumption responses to regional productivity shocks are non-linear; it depends on the household asset level and the idiosyncratic shock received by the household. This could be seen from the consumption policy function, which is a function of both z_i and B_i. In this exercise, I study the model-implied average consumption response to a 1 percentage point regional productivity shock, under both a recession period (negative aggregate productivity and positive risk shocks) and a expansionary period (positive aggregate productivity and negative risk shocks), using an empirical estimation of the simulated data. Additionally, to separately study the role of state-contingent fiscal transfers, I also compare the baseline model economy with a state-contingent fiscal transfer rule to an alternative without it.

Specifically, I simulate the model economy in four different settings: with or without state-contingent transfers, recession or expansionary episode. In the model economies with state-contingent transfers, the transfer policy coefficient ϑ_y is set to be the baseline value; whereas in those without, it's set equal to 0, indicating equal transfers across each region regardless of its economic situation. Recession episodes are defined as the combination of a negative one standard deviation aggregate productivity shock and a positive shock to regional risk, reaching the level of σ_z^H. Expansionary episodes are defined as the combination of a positive one standard deviation aggregate productivity shock and a negative shock to regional risk, reaching the level of σ_z^L. I then project consumption on regional shock conditional on household asset using local projection method, to get an average impulse response of consumption to regional productivity shocks, depicted in Figure 7.

The left panel of Figure 7 corresponds to an economy without state-contingent transfers. Upon realization of a 1 percentage point regional productivity, consumption in the recession episode rises by around 0.4 percentage point before gradually reverting back the original steady state. While in the expansionary episode, though the pattern of consumption responses looks similar, the initial and ensuing responses are much lower. This implies that during recessions risk sharing tends to worsen. The consumption policy shows that marginal propensity to consume tends to be larger for households that received bad shocks, which is the case for a recession. That's why consumption is more sensitive to a positive regional shock during a recession episode. This is not inconsistent with the fact that when there's higher risk, households tend to save more, because the impact of lower productivity dominates, making more people inclined to deleverage, and more people constrained at the borrowing constraint.

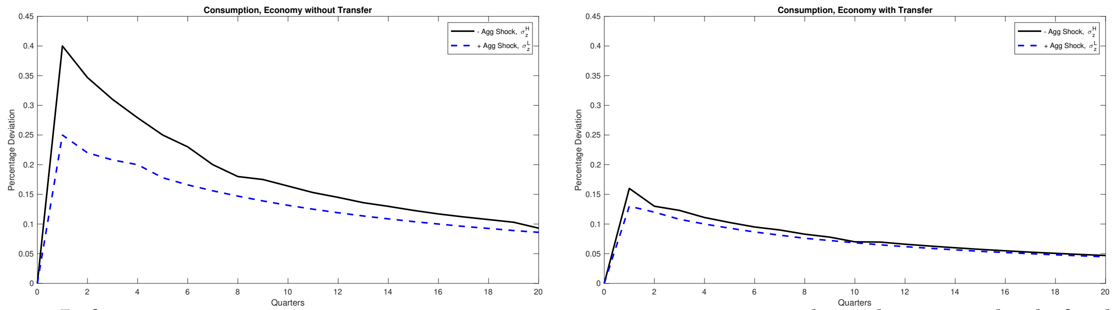
The right panel of Figure 7 depicts the consumption dynamics in an economy with state-contingent transfers. Two messages are delivered by this picture. First, the previous comparison between recession and expansion still holds although the difference between these two episodes is much smaller. Second, when compared with the economy without state-contingent transfers, the consumption is less than half as sensitive to regional shocks in the transfer economy. Both observations indicate the power of fiscal transfers in providing risk sharing across regions, although during recessions the combination of negative productivity shock and increased regional risk tends to worsen it.

Aggregate Productivity Shock

Now let's turn to a different measure of risk sharing, namely the consumption dispersion. I simulate the economy at the stationary equilibrium as well as when the economy is hit by a negative productivity shock. This shock comes with an additional aggregate shock, the regional risk shock. I calculate the dynamics of the standard deviation of consumption and plot them in Figure 8.

In both economies, with or without transfer contingency, dispersion of consumption rises upon realization of the negative productivity shock. This could be explained by two reasons. The first reason is that when a negative shock hits the economy, a larger fraction

Figure 7: Consumption Response to Regional Productivity Shocks



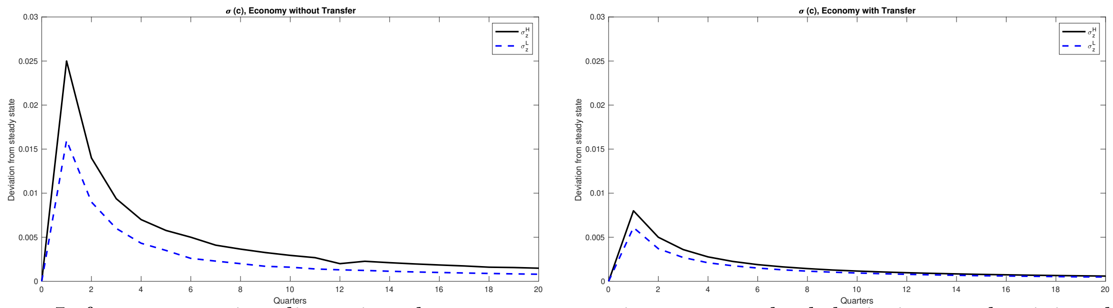
Notes: Left: consumption responses to a +1 percentage point regional productivity shock for both a recessionary episode and expansionary episode, in an economy with state-contingent fiscal transfer policy. Right: consumption responses to a +1 percentage point regional productivity shock for both a recessionary episode and expansionary episode, in an economy without state-contingent fiscal transfer policy.

of regions will be constrained by the borrowing constraint. Not being able to borrow makes the households at the lower end of the wealth distribution really worse off and it also exacerbates risk sharing arrangements. Secondly, upon realization of the shock, the dispersion of marginal propensity to consume rises: MPC for the households in poor regions increases dramatically, while it stays almost unchanged for those in wealthy regions. When the productivity shock comes with higher regional risk, more regions tend to receive very bad shocks, making risk sharing worse in this scenario. Comparing across the two economies, the economy with transfer contingency experiences much muted change in consumption dispersion, again indicating the stabilization effects of state-contingent fiscal transfers.

1.5.5 Counterfactual Analysis

Do the patterns of regional risk and regional risk sharing matter to the aggregate fluctuations? And what role does the fiscal transfer play? To understand the aggregate implications of regional risk, regional risk sharing, and government fiscal transfer policies on the aggregate fluctuations, which is the core question of the second-half of this paper, I conduct several counterfacutal exercises to quantify each channel in isolation.

Figure 8: Dispersion of Consumption to Aggregate Productivity Shocks



Notes: Left: consumption dispersion changes to a negative one standard deviation productivity shock when the productivity shock is accompanied with higher or lower risk, in an economy without transfer contingency. Right: consumption dispersion changes to a negative one standard deviation productivity shock when the productivity shock is accompanied with higher or lower risk, in an economy with transfer contingency.

In this paper, the primitive shock that generates a recession is the aggregate productivity shock. This supply-side shock, however, does not capture the whole picture of a recession at least for the most recent one. In fact, a large number of papers studying the 2008 Great Recession have attached importance to the financial frictions, aggregate demand shocks, government spending and so on. I choose productivity as the primitive shock primarily to be consistent with the classical business cycle framework, and ask: if we allow for the additional channels studied here, what difference will they make in generating the aggregate fluctuations, relative to the plain vanilla business cycle framework without these considerations? In that regard, this exercise is not meant to be realistic but done to gain insight on the new observations we made; and this approach is in the same spirit of many papers exploring the new mechanisms of business cycles, such as Bloom et al. (2018). Despite this concern, this exercise could quantify how much the baseline model economy could explain what happened in the actual economy during the Great Recession.

I start by describing how the aggregate TFP shocks are estimated. I take the total factor productivity data from John Fernald's website. This dataset contains quarterly estimates of TFP growth for U.S. business sectors ranging from 1947Q2 to 2019Q2. TFP shocks are generated in two steps. First, I detrend the TFP levels using either linear detrending or HP filter method. Second, I fit a AR(1) process to the detrended TFP data. The residuals of this regression are the TFP shocks plotted here in Figure 9 for 2008-2012 and Figure 28 in the Appendix for the whole sample. It turns out that the estimated shocks are not sensitive to the exact detrending method.

From 2008Q1 to 2009Q2, the TFP shocks have been below 0, reaching the minimum value in 2008Q4. Since 2009Q2, these shocks start to turn positive and fluctuate around 0. This timing accords with the that dated by the NBER recession committee, where the peak was dated 2007Q4 and the trough being 2009Q2.

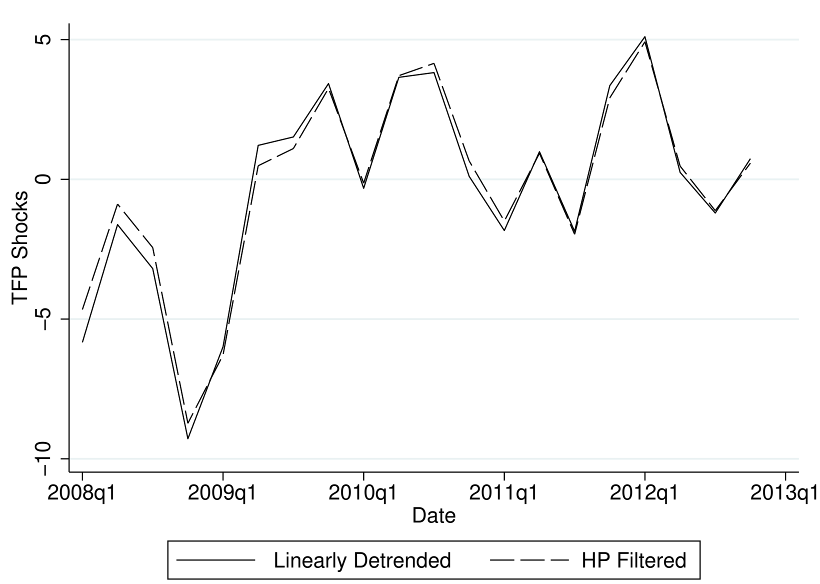
Fed with the actual TFP shock realizations between 2008 and 2012, the baseline model broadly generates the pattern of the data. In the left panel of Figure 10, I plot the fluctuations in GDP in the model vs. the data. In this figure, 2017Q4 was set as the starting year with GDP normalized to 0. Since the onset of this recession, GDP plummeted dramatically by more than 5 percentage points till the trough in 2009Q2. After that, it started to recover but very gradually. The baseline model broadly gets this pattern right, although the magnitude of fall in output was only about 4 percentage points. As mentioned above, a number of mechanisms may have contributed to the Great Recession which are not addressed in this paper, such as the financial market frictions and housing market collapse, hence it's hopeless to perfectly match the model with the data and it's not the intention of this paper to do so. Nevertheless, the baseline model is able to explain around 80% of the peak-to-trough fall in aggregate output during the Great Recession.

The right panel of Figure 10 presents the key counterfactual results. The baseline economy is the one with increased regional risk during the recession together with state-contingent transfers. In the baseline economy, asset market is incomplete. To quantify the aggregate impact of imperfect regional risk sharing, I build and simulate a counterfactual economy where the asset market is complete, where regions could perfectly share idiosyncratic productivity risks. I feed the same series of productivity shocks into this economy, and plot the aggregate output series simulated from this economy (blue dashed line). The maximum decline in output in the counterfactual economy is 0.9 percentage point lower than the baseline (–3.1 vs. –4). Put differently, imperfect risk sharing has amplified the aggregate fluctuations in output by 0.9 percentage point. This result is consistent with the main message delivered by Berger et al. (2019), who find that deviations from perfect risk sharing were an important determinant of the behavior of aggregate demand during the U.S. Great Recession, using household-level data and a entirely different quantification strategy than this one.

To separately identify the importance of increased regional risk and federal fiscal transfers on the aggregate fluctuations, I conduct two more counterfactual exercises. First, I simulate an economy identical to the baseline configurations except that regional risk doesn't go up. I find that the peak fall of aggregate GDP was –3.4 percentage point in this counterfactual economy. This implies that the increased regional risk has amplified the aggregate fluctuations by 0.6 percentage point. Second, I simulate another counterfactual economy without a state-contingent fiscal transfer rule, i.e. set ϑ_y equal to 0. In this economy, the maximum fall in output was 4.4 percentage points, a 0.4 point higher than the baseline. This results says that the federal fiscal transfers indeed has stimulated the aggregate demand, and it dampened the impact of an aggregate productivity shock on the aggregate output.

Combining this with the impulse response results in Section 1.5.4, three conclusions are drawn. First, increased regional risk together with negative productivity shocks tend to worsen regional risk sharing during a recession, however the fiscal transfer contingency help stabilize the regional economies by providing insurance through the government. Second, despite that the degree of regional risk sharing is high and tends not to fluctuate over the business cycle, its imperfectness still contributed nearly 1 percentage point in amplifying the aggregate output drop. Third, increased regional risk amplified the aggregate fluctuation by 0.6 percentage point, due to stronger precautionary saving motives of the households; fiscal transfers worked in the opposite direction, dampening it by 0.4 percentage point, and it did so by providing insurance to the regions that need it the most (high MPC), thus more effectively stimulating the aggregate demand.

Figure 9: TFP Shocks 2008-2012



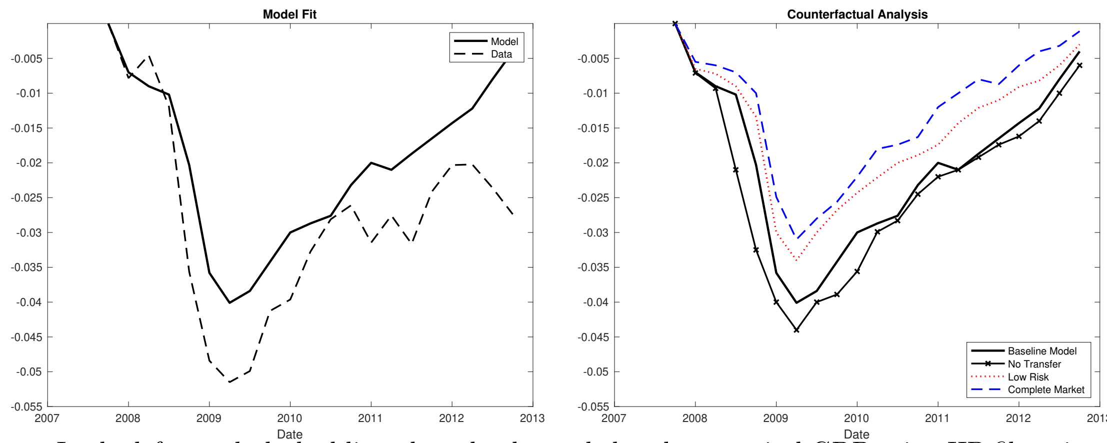
Notes: Sample period: 2008Q1-2012Q4. TFP series are retrieved from John Fernald's website. To obtain TFP innovations plotted here, I first detrend the TFP either using a linearly detrending method (solid line) or using HP filters (dashed line). I then fit an AR(1) process to the detrended data. The noises to the AR(1) process are the TFP shocks.

1.5.6 Sensitivity Analysis

The quantitative results presented in the previous section may be sensitive to the parameter values chosen. In this section, I present the sensitivity analysis results by varying the parameters one at a time. Table 7 presents the impact of changing each parameter value on the steady-state distribution of consumption (a risk sharing indicator) and the impulse response of aggregate output to a negative aggregate productivity shock using the baseline configurations. The former is presented in percent changes while the latter in absolute changes in percentage points.

Lowering the regional shock persistence from 0.9 to 0.7 improves risk sharing, lowering the dispersion of consumption in the stationary equilibrium 5.6%. Related to that,

Figure 10: Model Fit & Counterfactual Results



Notes: In the left panel, dashed line plots the detrended real per capital GDP using HP filter, in which 2007Q4 was normalized to 0. The solid line plots aggregate output generated by the baseline model. In the right panel, solid line stands for the baseline economy, solid line with "x" for the counterfactual economy without state-contingent transfer, dotted line for the counterfactual economy with lower risk σ_z^L, and dashed line for the counterfactual economy with a complete asset market.

the initial output response rises by 0.2 percentage point, that is, the magnitude of decline is lower. It's well known that transitory shocks are easier to insure against than permanent ones, and this result exactly reflects this point. After changing ϑ_y from the OLS estimate to IV estimate, steady state risk sharing improves (decline in dispersion), and the initial response to productivity shock is lower by 0.6 percentage point. When the federal fiscal policy becomes even more "state-contingent", risk sharing improves and the dampening effect of fiscal transfer is stronger. Impacts of the productivity shock may be determined by how aggressive monetary policy is (a similar point was made in (McKay and Reis, 2016)). A less accommodative monetary policy rule has negligible impacts on risk sharing, but it amplifies the impact of productivity shocks. However, it remains to be seen how this change affect the impact of fiscal policy and I leave it for future work. Trade elasticity η has an impact on regional risk sharing too. Changing the trade elasticity from 0.5 to 2, regional risk sharing has improved. However, this sensitivity result should not be taken at face value as trade elasticity might interact with other factors in determining the regional risk sharing. For example, Corsetti et al.

(2008) argue that how trade elasticity affects international risk sharing depends on the persistence of productivity shocks. The aggregate fluctuation is nevertheless not sensitive to this parameter change. Lastly, varying the borrowing limit from 0.3 to 0, thus loosening the credit constraint, strongly improves regional risk sharing and dampens the aggregate impact of the productivity shock.

Table 7: Sensitivity Analysis

Parameters	Baseline Values	New Values	% Change in SS $\sigma(C)$	Change in Baseline IRF
ρ_z	0.90	0.70	–5.6	+0.2 p.p.
ϑ_y	–0.33	–0.624	–9.8	+0.6 p.p.
ϕ_π	1.5	1.1	0.1	–0.2 p.p.
η	0.5	2	–1.3	+0.05 p.p.
b	0.3	0	–11.6	+0.62 p.p.

1.6 Conclusion

In light of the wide dispersion of regional output growth rates suggesting the existence of region-specific shocks, a natural question to ask is: what does the distribution of regional shocks look like over the business cycle? I empirically approach this question combining a U.S. state-level dataset and a GMM estimation strategy to identify the persistence and conditional standard deviations of regional shocks (regional risk), assuming that regional income (growth or detrended) is driven by three components: a long-run term, a regional shock, and an aggregate shock. I find that the persistence of regional shocks is tantamount to that of the aggregate ones. Moreover, regional risk is estimated to be 40% larger in NBER recessions than in normal times.

Although dispersion of output growth surges during recessions, in line with increase in regional risk, that of consumption does not, suggesting that risk sharing stays strong in a recession. I formally test the pattern of regional risk sharing using the aforementioned GMM framework and the classic OLS regressions, the results of both delivering the same message: the degree of risk sharing is no different in recessions than in normal times. This result calls for other channels through which risk sharing might be improved during a recession. And this paper highlights the role of state-contingency in federal fiscal transfers. The share of unemployment insurance, a natural "state-contingent" instrument, grows rapidly in recessions, which helps explain why the federal government transfers have effectively targeted the depressed regions during the these periods but not in normal times.

How do the patterns of regional risk, regional risk sharing and federal government transfer policy interact with each other and how much do they affect the aggregate fluctuation? To address this question, I build a heterogeneous-regions model that features incomplete asset market, time-varying regional productivity risk, and federal government transfers that are operated in a state-contingent way. The model shows that during an economic downturn, while increased regional risk exacerbates risk sharing due to more regions being constrained at the borrowing limit, state-contingent federal government transfers substantially reduces the dispersion of consumption by targeting regions with low productivities. This increase in regional risk also depresses the aggregate demand due to stronger precautionary saving motives. Yet the fiscal policy effectively undoes this impact by providing insurance to the regions that need it the most, that is, regions with the highest marginal propensity to consume. The special feature of the U.S. fiscal policy uncovered in this paper thus offers a complementary channel in understanding how automatic stabilizers in fact stabilize the aggregate economy.

There are several interesting research directions following the current work. First, in this paper regional heterogeneity is entirely summarized by regional shock to income or output. It would be interesting to study the nature of the countercyclical regional risk by looking at various dimensions of heterogeneities alluded to in the introduction part. Second, to succinctly capture the essence of the two key ingredients, that is, regional risk and fiscal transfers, I've deliberately assumed away capital and government spending in the quantitative model, the dynamics of which would likely make a difference in aggregate output fluctuations as well. Third, this paper argues that the federal fiscal transfer is a powerful tool in restoring risk sharing during an economic downturn. However, there likely exists other channels promoting regional risk sharing especially in recessions. I leave them for future examinations.

Chapter 2

A Quarterly Dataset of US State-Level Aggregates (joint with Noah Williams)

2.1 Introduction

Regional level macroeconomic analysis is usually constrained by the lack of high-quality data, especially at a higher frequency. For example, most of the macro data at the state level are either missing, incomplete, measured with substantial measurement errors, or only available at low frequency, thus not suitable in studying many macro issues, which typically rely on data at a quarterly frequency (or higher). In the first half of this paper, we introduce a novel estimation framework to deal with the state-level macroeconomic data that feature: mixed-frequency across variables, measurement error, within-variable changes in data frequency, and missing data in early samples. To estimate this model, we employ the mixed-frequency VAR method proposed by Schorfheide and Song (2015) and augment it by allowing for measurement errors for each variable to potentially vary with changes in its data source. As in Aruoba et al. (2016) and Amir-Ahmadi et al. (2016), among many others, we use standard Bayesian estimation methods to jointly estimate the state-space model parameters and measurement error process parameters. Thus, our estimation approach combines the mixed-frequency and measurement error estimations by laying out a state-space model which is jointly estimated with a Bayesian estimation approach.

To illustrate potential applications of this dataset, we apply the estimated quarterly dataset of state-level macroeconomic variables to studying the transmission of monetary policy shocks to the state economy, in particular, output and prices. While there's a lengthy list of papers that study the transmission of monetary policy shocks to the aggregate economy, few of them study the state-level response to monetary policies due to lack of data. Some of recent literature focus on how one factor may drive differential monetary policy effects across regions, for example Beraja et al. (2019) study how regional difference in housing equities lead to different effects of monetary policy across regions. However, this paper provides an *overall* estimate of the monetary policy transmission at the state levels, regardless of its underlying driving factors.

Our estimation is based on the narratively identified monetary policy shocks proposed by Romer and Romer (2004). In order to separate the endogenous response of policy to information about the economy from the exogenous shock, they regress the intended funds rate change on the current rate (identified narratively) on the Greenbook forecasts of output growth and inflation over the next two quarters. The residuals of this regression are the so-called Romer-Romer shocks. These shocks capture the exogenous, or unanticipated components of monetary policy changes that are useful in making credible inferences.

We incorporate the Romer-Romer shocks in a structural VAR estimation that also includes log output and log consumer prices at the state level. Our main interest is the impulse responses of output and price to the monetary policy shock. We find that states behave remarkably consistent with each other in their responses to an unanticipated monetary policy shock, in terms of both qualitative and quantitative dynamics. Moreover, the responses closely track most of the features of their counterparts estimated with national data: output responses are hump-shaped peaking around 10 quarters after the initial monetary policy shock; prices stay insignificant for the first several quarters and then decline gradually until the end of the sample horizon.

2.2 The Model

Data. $x_{i,t} = (x^a_{i,t}, x^q_{i,t})'$. $x^a_{i,t}$ denotes the $1 \times n_a$ vector of variables available only at the annual frequency: real GDP, real consumption, real capital, state government expenditure, CPI; $x^q_{i,t}$ is a $1 \times n_q$ vector for variables available at the quarterly frequency: personal income, state tax revenue, total non-farm employment, and unemployment rate. All variables but the unemployment rate are in log terms.

$x_{n,t}$ is a vector of national variables that is assumed to be exogenous to the state economy. We obtain the S&P 500 Index from "CRISP Index File on the S&P 500". All the rest are from FRED. Quantity variables enter our analysis in real terms (chained 2009 Dollars). All the macro series are also seasonally adjusted. We convert, if needed, the high-frequency series to the quarterly frequency. Data sources for the national variables are listed in Table 14.

Measurement Error. Observation of variable j at time t for state i is denoted by $\widetilde{x^j_{i,t}}$, which is measured with errors. Suppose that:

$$\widetilde{x^j_{i,t}} = \widehat{x^j_{i,t}} + m^j_{i,t} \tag{2.1}$$

where $\widehat{}$ denote the "true" data, free from measurement errors. We allow the variance of the measurement error terms to vary with the underlying data sources. For example, 1997 is a break point when the BEA PCE data started to be available and when BEA switched from SIC to NAICS. Table 8 displays a summary of the break points in our sample.

State-Transition Equation. We assume that true data (all in quarterly frequency) in *each* state economy evolves according to the following *state-transition equation* :

$$x_{i,t} = \sum_{l=1}^{L_s} \Phi^s_{i,l} x_{i,t-l} + \sum_{l=0}^{L_n} \Phi^n_{i,l} x_{n,t-l} + \Phi^c_i + u_{i,t}, u_{i,t} \sim i.i.d. N(0, \Sigma_i) \tag{2.2}$$

$\Phi^s_{i,l}$ and $\Phi^n_{i,l}$ are the coefficients on lagged state and national variables respectively; Φ^c_i is a vector of constants; L_s and L_n are the lags included in state and national variables; the innovation vector $u_{i,t}$ is assumed to be $i.i.d.$ and follow a multivariate normal distribution.

Table 8: Data Source Break Points

State-Level Variable	First Break Point	Second Break Point	Third Break Point
GDP	1988(1972SIC to 1987SIC)	1997 (SIC to NAICS)	2005Q1 (Annual to Quarterly)
Consumption	1997 (From Survey to BEA Data)	-	-
Capital	-	-	-
State Government Expenditures			
Consumer Price Index	-	-	-
Personal Income	-	-	-
State Tax Revenue	-	-	-
Total Nonfarm Employment	-	-	-
Unemployment Rate	-	-	-

Define $z_{i,t} = \left(x'_{i,t}, x'_{i,t-1}, ..., x'_{i,t-L_s}\right)'$, $z_{n,t} = \left(x'_{n,t}, x'_{n,t-1}, ..., x'_{n,t-L_n}\right)'$, $\Phi_i^s = \left(\Phi_{i,1}^s, \Phi_{i,2}^s, ..., \Phi_{i,L_s}^s, \Phi_i^c\right)'$, $\Phi_i^n = \left(\Phi_{i,0}^n, \Phi_{i,1}^n, ..., \Phi_{i,L_n}^n\right)'$, and let's rewrite Equation (2.2) in the following companion form:

$$z_{i,t} = F^s(\Phi_i^s) z_{i,t-1} + F^n(\Phi_i^n) z_{n,t} + F^c(\Phi_i^s) + v_{i,t} \tag{2.3}$$

Measurement Equation. The vector of quarterly series $x_{i,t}^q$ is observed every quarter:

$$\widehat{x_{i,t}^q} = x_{i,t}^q = \Lambda_{q,z} z_{i,t} \tag{2.4}$$

Suppose the underlying quarterly VAR has at least 4 lags, we express the 4-quarter average of $x_{i,t}^a$ as:

$$\overline{x_{i,t}^a} = \frac{1}{4}\left(x_{i,t}^a + x_{i,t-1}^a + x_{i,t-2}^a + x_{i,t-3}^a\right) = \Lambda_{a,z} z_{i,t} \tag{2.5}$$

Note that the four-quarter average is observed only every fourth quarter. The relationship between $\overline{x^a_{i,t}}$ and $x^a_{i,t}$ is as follows:

$$\widehat{x^a_{i,t}} = M_{a,t}\overline{x^a_{i,t}} \tag{2.6}$$

$M_{a,t}$ is a selection matrix that equals the identity matrix if t is the last quarter of a year and is empty otherwise. Combine Equations (2.1) (2.4) (2.5) and (2.6), the measurement equation of our model system is:

$$\widetilde{x_{i,t}} = M_t \Lambda_t z_{i,t} + m_{i,t} \tag{2.7}$$

In M_t and Λ_t, the blocks corresponding to annual variables are given by $M_{a,t}$ and $\Lambda_{a,z}$; while the blocks corresponding to quarterly variables are given by identity matrix and $\Lambda_{q,z}$.

Taken together, the state-space representation of our model is given by Equation (2.3) and (2.7). The parameters to estimate are the VAR coefficients $\Phi_i = (\Phi_i^{s\prime}, \Phi_i^{n\prime})'$, covariance matrix for VAR innovations Σ_i, and variance of measurement error for each variable j $\sigma^j_{i,t}$.

Identification Assumptions. For simplification, we make the following assumptions in estimating the model.

Assumption 2.1. *Time-invariant VAR parameters and innovation volatilities.*

Assumption 2.2. *The innovation vector $u_{i,t}$ is uncorrelated with measurement errors $m^j_{i,t}$: $\rho(u_{i,t}, m^j_{i,t}) = 0$.*

Assumption 2.3. *Measurement error terms are Gaussian, and are independent over time and across variables: $m^j_{i,t} \sim i.i.d.N(0, \sigma^j_{i,t})$*

2.3 Estimation Approach

Since we estimate each state separately following the same estimation approach, we drop the i subscript without sacrificing clarity. We use the Bayesian estimation methods to estimate: 1. the model parameters (Φ, Σ, σ_t); 2. latent states $Z_{0:T}$. We generate draws from the posterior distribution of the model parameters $(\Phi, \Sigma, \sigma_t) \mid \left(Z_{0:T}, \widehat{X}_{-L_s+1:T}\right)$ and the posterior distribution of the latent states $Z_{0:T} \mid \left(\Phi, \Sigma, \sigma_t, \widehat{X}_{-L_s+1:T}\right)$ using the Gibbs sampling algorithm. The novel part here relative to Schorfheide and Song (2015) is to have one additional Gibbs step for drawing the measurement errors and its variances.

As in Amir-Ahmadi et al. (2016), the priors for the measurement error parameters are set similarly to Cogley et al. (2015). We assume that the priors are the same for each data source, but vary across variables to take into account the different volatilities of each variable. We use independent inverse-gamma priors for measurement error variance σ_t^2. The prior for VAR parameters (Φ, Σ) is set as the Minnesota prior, following the VAR literature (Sims and Zha, 1998; Schorfheide and Song, 2015). In particular, our choice of the prior for (Φ, Σ) belongs to the family of multivariate normal inverted Wishart (MNIW) distributions. One advantage of this class of distributions is to reduce the high dimensionality of parameters to a low-dimensional hyperparameter λ, which controls the distribution.

Conditional posterior distribution of the VAR parameters, measurement error parameters, and latent states are as follows:

$$p\left(\Phi, \Sigma | \sigma_t^2, Z_{0:T}, \widehat{X}_{-L_s+1:T}, \lambda\right) \propto p\left(\Phi, \Sigma | \lambda\right) p\left(Z_{1:T} | z_0, \Phi, \Sigma, \sigma^2\right) \tag{2.8}$$

$$p\left(\sigma_t^2 | \Phi, \Sigma, Z_{0:T}, \widehat{X}_{-L_s+1:T}, \lambda\right) \propto prior(\sigma_t^2) p\left(Z_{1:T} | z_0, \Phi, \Sigma, \sigma^2\right) \tag{2.9}$$

$$p\left(Z_{0:T} | \Phi, \Sigma, \sigma_t^2, \widehat{X}_{-L_s+1:T}, \lambda\right) \propto p(\widehat{X}_{1:T} | Z_{1:T}) p\left(Z_{1:T} | z_0, \Phi, \Sigma, \sigma^2\right) p\left(z_0 | \widehat{X}_{-L_s+1:0}\right) \tag{2.10}$$

Because of our assumption of MNIW distribution for VAR parameter priors, their posterior distribution given by (2.8) also follows a MNIW distribution. Draws from this posterior are obtained by direct Monte Carlo sampling. Similarly, posterior distribution of the measurement error variance given by (2.9) also follows an inverse-gamma distribution, from which we may sample using Monte Carlo methods. Sampling from the posterior distribution of latent states given by (2.10) follows a standard treatment of the simulation smoother in linear Gaussian state-space models.

Sampling from the three conditional densities above using Gibbs sampling algorithms, we may get posterior estimates of the parameters and the latent states conditional on observations of the mixed-frequency data.

2.4 Monetary Policy Analysis

While there are many ways in which our estimated quarterly state-level data could be applied, an interesting application is to study the state-level responses to an unanticipated monetary policy shock.

Studying the macroeconomic effect of a monetary policy shock is a classic question in macroeconomics. Both the 1999 and 2016 Handbook of Macroeconomics chapters have extensive summaries of this literature at those points of time (Christiano et al., 1999; Ramey, 2016). In particular, there are two recent approaches to dealing with this question: 1. The "recursiveness identification assumption", for example Christiano et al. (1996). They use a particular form of the Cholesky decomposition in which the first block of variables consisting of output, prices, and commodity prices was assumed not to respond to monetary policy shocks within the quarter (or month); 2. Using "externally identified monetary policy shocks", for example Romer and Romer (2004)'s narrative/Greenbook shock, and Gertler and Karadi (2015)'s recent high frequency identification shocks identified using fed funds futures. Despite the difference in methodologies, a standard finding in the literature is that monetary policy shocks have significant and persistent impact on output and prices, although its magnitude and speed of recovery are under debate.

Much less attention has been focused on the monetary policy impacts at more disaggregated regional levels until recently. For example, Beraja et al. (2019) find that monetary policy has differential impacts on regional consumption demand depending on regional housing equity via its consequence in the mortgage refinancing responses. They in turn argue that the aggregate response of monetary policy depends on the distribution of equity across space. In fact, studying the regional response to a common monetary policy shock also may help us better understand the sources of regional inequality.

In this Section, we first describe our estimation approach and then discuss the state-level responses to monetary policy shocks.

2.4.1 Approach

Our baseline estimation is based on Romer and Romer (2004), who combine the use of Greenbook forecasts with narrative methods to construct a new measure of monetary policy shocks. In particular, their monetary policy shock series are estimated as residuals from a regression of the federal funds rate on lagged values and the Federal Reserve's information set based on Greenbook forecasts. First, they derive a series of 34 intended federal funds rate changes during FOMC meetings using narrative methods. Second, in order to separate the endogenous response of policy to information about the economy from the exogenous shock, they regress the intended funds rate change on the current rate and on the Greenbook forecasts of output growth and inflation over the next two quarters. They then convert the estimated residuals based on the FOMC meeting frequency data to monthly and used them in dynamic regressions for output and other variables. They found very large effects of these shocks on output.

In the following studies, we use the updated quarterly-frequency Romer-Romer shock series by Wieland and Yang (2020) that range between 1969Q1 and 2007Q4.

We estimate a structural VAR to study the impact of monetary policy shocks on state-level GDP and price:

$$X_t = A_0 + A_1 X_{t-1} + A_2 X_{t-2} + ... + A_p X_{t-p} + \varepsilon_t \tag{2.11}$$

And

$$\varepsilon_t = B s_t \tag{2.12}$$

where X_t is ordered by log GDP, log CPI and Romer-Romer monetary policy shocks; ε_t denotes the VAR disturbances; s_t denotes the structural shocks. The constraints on A_i and B also follow the assumption in Romer and Romer (2004), which in turn is based on Christiano et al. (1996)'s recursive identification strategy: monetary policy is assumed to respond to, but not to affect, the other variables contemporaneously. We include three years of lags in our baseline specification, that is, $p = 12$.

2.4.2 Result

Before showing our state-level result, it's useful to review the basic findings in Romer and Romer (2004). In their baseline VAR specification, a positive monetary policy shock first leads to a rise of output by a small amount for the first two months, then falls sharply through month 23, and then returns toward its initial level. The peak effect is highly statistically significant. The response of prices implied by the VAR is small, irregular, and insignificant for eight months, and then negative. The monetary policy innovation lowers the price level gradually over a four-year horizon. So the response of price is persistent.

Now let's turn to the state-level results. In Figure 11 and Figure 13, we show the impulse responses of output and consumer price to a +1 standard deviation shock to monetary policy, identified by the Romer and Romer (2004) narrative methods. The solid lines show the average estimate of the impulse responses, and the dashed lines show the one-standard-error bands, or 68% confidence intervals. Since both GDP and

CPI enter the VAR in logarithms, we could illustrate the impulse responses as percent changes in GDP and percentage changes in inflation.

There are two observations from the result regarding output responses. First, with only a few exceptions, namely AK, KS, LA, OK, WV and WY, there are similar hump-shaped responses of GDP in most states, with the peak effect occurring consistently at the tenth quarter: roughly the same timing as the national estimation. Second, there's slight variations across states regarding the magnitude of output responses, but most of them lie within one percent level in a 5-year horizon.

Turning to price responses, there's almost a uniform change in price dynamics across the states. As with the result using aggregate data, state-level prices first stay insignificantly different from zero or weakly positive for a period of around 10 quarters, before falling down all the way towards the end of the 5-year horizon (WI and WV are the two exceptions). Compared with GDP, the difference in the magnitude of price responses is even smaller: most states experience a decline in consumer price by around 0.5% five years after the monetary policy shock.

Our result suggests that, on average monetary policy has very similar impacts on either output or consumer prices across states. This is a surprising result given the substantial heterogeneity at various dimensions like economic structure, population composition etc. which all might have led to differences in the transmission of monetary policy shocks to the states. This result is also in sharp contrast with what we find in studying state-level fiscal policy implications in Liu and Williams (2019), who find that there's substantial heterogeneity across states in the output and employment responses to federal tax shocks. In particular, more than half of the states do not have significant response of output or employment to federal tax shocks; while for those states that do respond significantly, the magnitude of responses also varies widely.

There are also some differences between state-level estimates and national ones that are worth noting. First, unlike the result shown in Romer and Romer (2004), with few exceptions state-level output do NOT expand in the first several quarters after a contractionary monetary policy: in most states, output starts to decline right after being hit by the shock. Second, unlike the results estimated using national data, output has a bigger negative response than price in most states; while the maximum percentage drop in prices is almost twice the drop in output. These observations are both worth investigating at greater length.

2.5 Conclusion

In this paper, we first introduce a novel estimation framework to deal with the state-level macroeconomic data that feature: mixed-frequency across variables, measurement error, within-variable changes in data frequency, and missing data in early samples. We use standard Bayesian estimation methods to jointly estimate the state-space model parameters, time-varying measurement error variances, and the unobserved latent quarterly components of variables that are observed only annually.

As one application of this quarterly dataset of state-level macroeconomic variables, in the second half of the paper we study the transmission of monetary policy shocks to the state economy, in particular, output and prices. It turns out that states behave remarkably consistent with each other in response to an unanticipated monetary policy shock. Moreover, these responses closely track most of the features of their counterparts estimated with national data: output responses are hump-shaped peaking around 10 quarters after the monetary policy shock; prices stay insignificant for the first several quarters and then decline gradually until the end of our sample horizon.

For future work, it would be interesting to investigate at length: 1. why a few states are the exceptions; 2. why does monetary policy has nearly homogeneous effects across states while tax policy has substantially heterogeneous ones.

Figure 11: Effect on State-Level Output

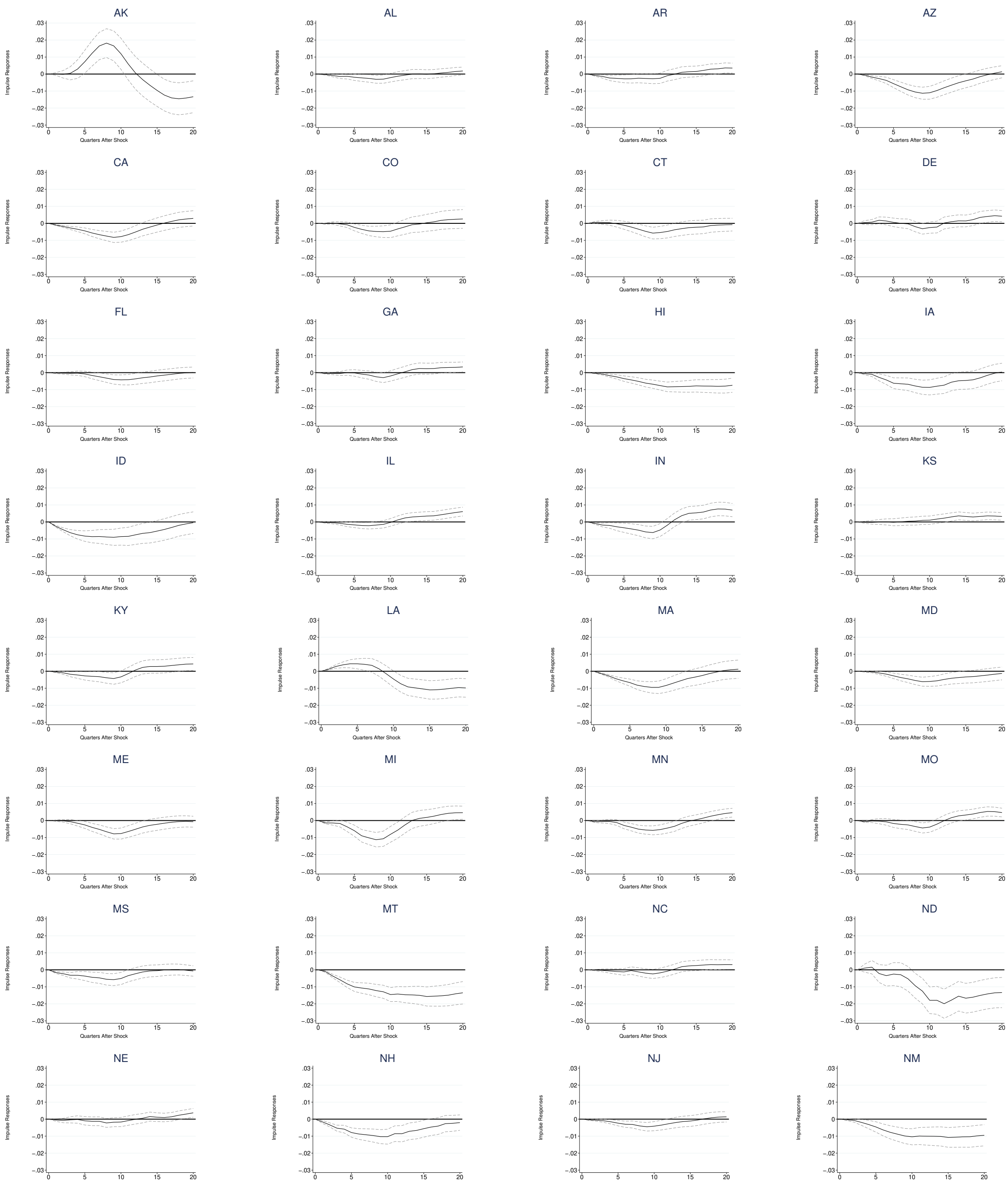


Figure 12: Effect on State-Level Output (Continued)

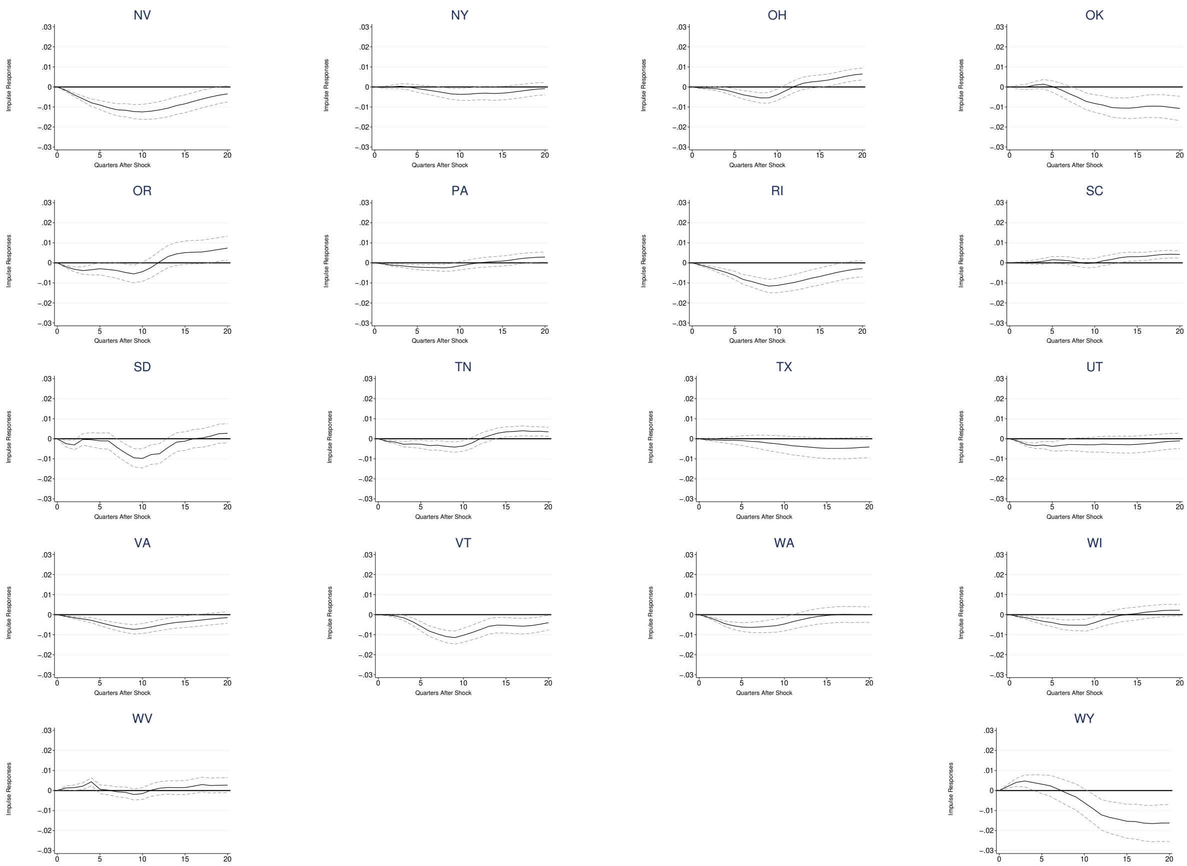


Figure 13: Effect on State-Level CPI

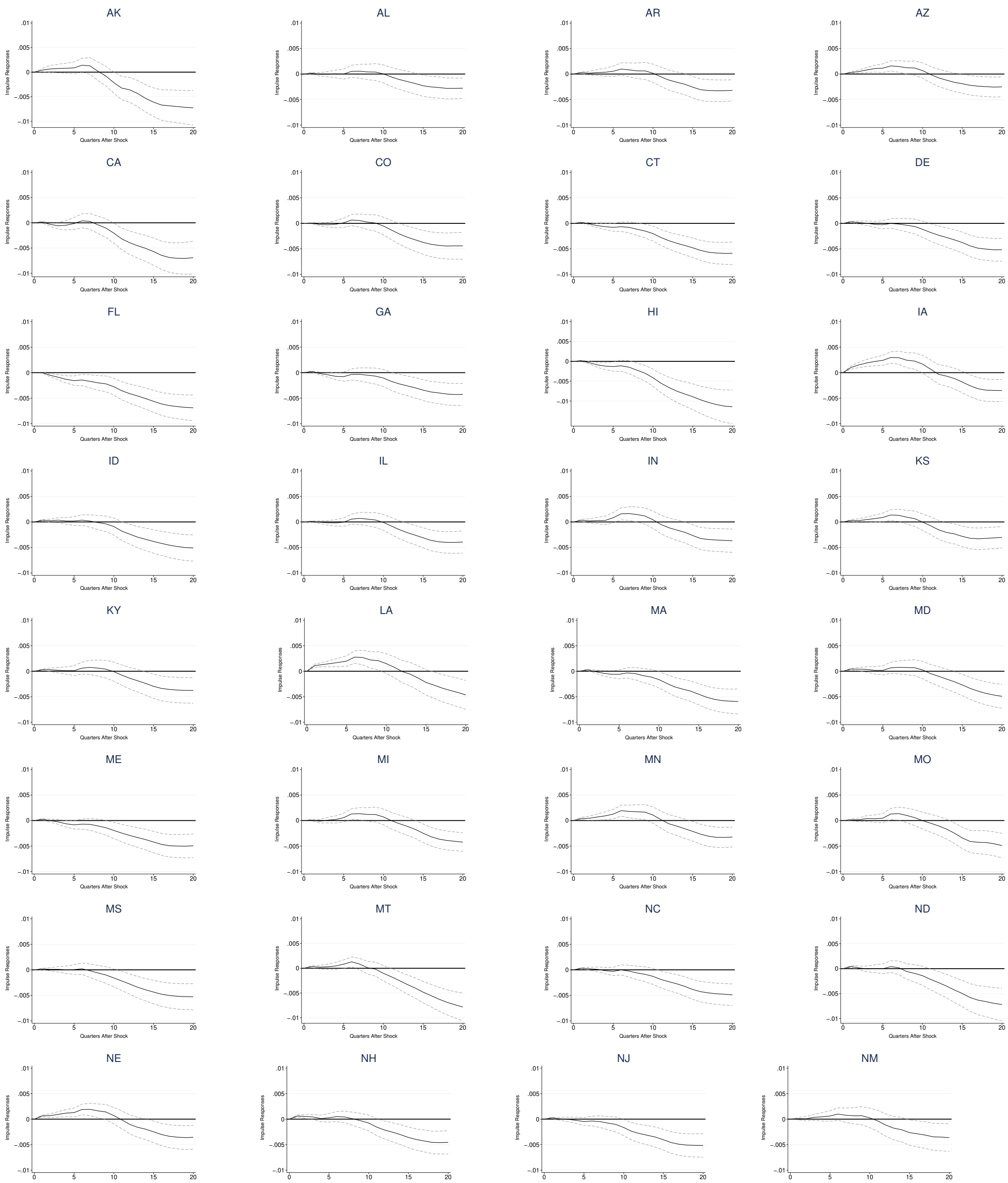
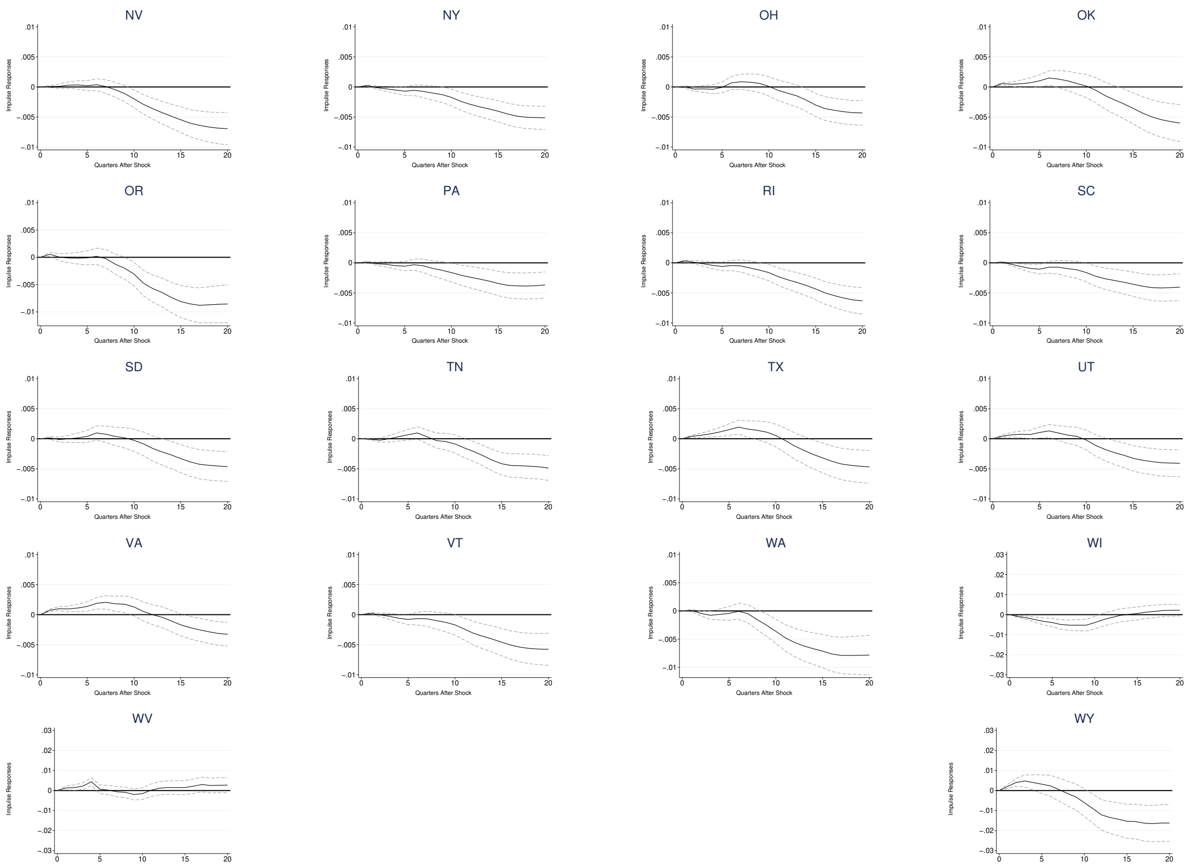


Figure 14: Effect on State-Level CPI (Continued)



Chapter 3

State-Level Implications of Federal Tax Policies (joint with Noah Williams)

3.1 Introduction

The United States provides a rich environment to study economic dynamics and the impact of economic policy. The states are the well-known "laboratories of democracy" and their differing experiences can shed light on a number of important issues. The diversity of different statewide and regional factors and policies allows for many interesting interactions and comparisons. In addition, the commonality of national factors, federal fiscal policy, and monetary policy can potentially allow for a clear isolation of sources of difference. In essence, the United States consists of a monetary and fiscal union, with fifty small open economies that each control an additional layer of state fiscal and regulatory policy. A growing body of research has used this regional variation across states to inform estimates of policy impacts and sources of fluctuations. In this paper we analyze the differential impact across states of changes in the common federal tax policy, which helps us understand the channels of policy impact.

Recent studies find large and significant *aggregate* expansionary effect of tax cuts, for example, Blanchard and Perotti (2002), Romer and Romer (2010), Mertens and Ravn (2013) among others. This paper builds on but departs from this literature by investigating the *regional* effects of unanticipated changes in both federal personal and corporate income tax, using more than 50 years of data at the state level. We find that given an unanticipated negative federal personal or corporate income tax shock, the output or employment responses are significantly positive for less than half of the states, not significantly different from zero for over a half of the states, and that a few states respond to neither tax change significantly. There are more states showing significantly positive output or employment responses to a corporate than personal income tax cut, but the average responses to the latter are higher. Our results imply that the positive aggregate output responses to either personal or corporate income tax cut, as found in various previous studies, may have been driven by only a small number of states. Therefore, it's important to look beyond the aggregate macro data and investigate the differential effects of a nationwide policy from a regional perspective. In particular, as we discuss below, our results suggest that factor reallocation across states and sectors plays an important role in generating the aggregate impacts of federal tax changes.

Our empirical results are drawn from two main datasets. First, we compile from various sources a state-level raw dataset of the key macro variables. However, most of the macro data at the state level are either missing, incomplete or only available at low frequency, thus not suitable in studying many macro issues, which typically rely on data at a quarterly frequency (or higher). We produce a relatively balanced state-level historical dataset, employing the mixed-frequency VAR method proposed by Schorfheide and Song (2015), who used it in a forecasting framework using aggregate data with different frequencies. Second, we extend the time series of narrative federal personal and corporate income tax shocks in Mertens and Ravn (2013), following Romer and Romer (2010)'s account of changes in US federal tax liabilities, and eliminating the "anticipated" tax policy changes with implementation lags longer than a quarter.

Our state-level estimation follows the "proxy structural vector autoregression (SVAR)" method described in Mertens and Ravn (2013). By proxying latent structural tax shocks with narratively identified tax liability changes of federal taxes in a SVAR framework, this methodology has obvious advantages in circumventing the strong identification assumptions in previous versions of SVAR, and the unavoidable measurement error issue in the narrative approach, see discussions in Mertens and Ravn (2014). In particular, we assume that the narrative tax changes are uncorrelated with macro fundamentals because of the way they are constructed, and allow them to be correlated with the structural tax shocks because of, say, measurement errors. As in Mertens and Ravn (2013), we impose additional restrictions between the reduced-form VAR residuals and the structural shocks in order to separately identify the effect of one tax shock controlling for the other one. We then make inferences on the impulse responses of state-level macro variables to either structural tax shock.

We find substantial heterogeneity in our point estimates of the responses of state output to either tax cut: the peak GDP increases range from 1% – 7% in response to a 1 percentage point cut in the average personal income tax rate, and 0 – 1.5% when there's a 1 percentage point cut in the average corporate income tax rate. Once considering the statistical significance of these estimates, we notice that more than half of the states do not have a significant response to either tax cut, even more striking evidence of state-level heterogeneity.

We proceed to study what state-level characteristics may explain these heterogeneous responses. We focus on two possible candidates: the state tax structure (measured by the average state personal income, corporate income and sales tax rates), and the state economic structure (measured by the overall capital share of income). States differ substantially in the overall level and composition of their tax systems, and when combined with federal taxes, this leads to different effective tax rates across states. Thus one may expect differential impacts of federal tax policies which operate on the same margins as federal taxes, as the state taxes are compounded by federal taxes. However we find relatively little evidence of this impact. The variation in state tax structure doesn't seem to consistently explain the heterogeneous state-level responses we observed.

Turning to the economic structure, McMurry and Williams (2018) document substantial heterogeneity in the factor intensities of production in different states. Industries are not uniformly spread across the United States, and this differential industry composition along with variation of factor-intensities within industries leads to different estimates of the state-level factor shares. Across several specifications, We find robust evidence that output responses to a 1 percentage point corporate tax cut are negatively correlated with the average state capital share of income across all of our specifications: a 1 percentage point higher capital share is associated with lower cumulative responses of output and employment, by 0.7 – 0.9% over a 5-year horizon.. Most of our specifications also show a negative relationship between the employment response to a corporate tax cut and capital share as well, albeit of a smaller magnitude.

This result is striking because it is runs counter to most standard macro models used to study the dynamic impact of taxation. In a standard one-sector model, it is natural to assume that all production is done by corporations. In this case, with competitive markets the corporate income tax is equivalent to a tax on capital income (making the common assumptions that investment is financed by equity). Thus we would expect the effect of a cut in the corporate tax to have the largest effect in economies (or states) which are most capital intensive. That is, states with a larger share of capital income use capital more intensively in production, and accumulate larger capital stocks. A reduction in the corporate tax thus affects a larger tax base, driving larger changes in incomes, and leading to a larger impact on output. We illustrate these effects in a number of one-sector models, showing that the conclusions are not affected by the details of the market structure, trade, or frictions. These additional features may affect the short-run impact of the tax changes, but are not enough to change the long-run or cumulative response.

While in one-sector models the corporate tax is a tax on capital, it is really a tax on the capital and profits of a particular type of business. In addition, although in the past most of US output was produced by corporations, this is no longer the case. In recent years the share of pass-through businesses, which are taxed as income to owners rather than through the corporate tax, has grown and now makes up a majority of economic activity. As we discuss, the traditional analysis of the incidence of corporate taxes, following Harberger (1962), focuses on the mobility of factors across sectors as well as states. Thus we focus on a small open economy model with the addition of a non-traded corporate sector, whose good (services, for example) must be supplied by domestic producers. We show that such a two-sector model can explain, at least qualitatively, our empirical finding of a larger output response to a corporate tax cut with a smaller capital's share of income. The key to this result in our model is that the larger overall capital's share in the state results from a disproportionate increase in the capital intensity of the non-corporate sector. Overall our results point to the importance of regional variation in understanding the impact of policy changes, and suggest that factor reallocation across states and sectors plays an important role in generating the aggregate impacts of federal tax changes. In a similar fashion to our work is Giroud and Rauh (2018), where they show that the legal form of business and reallocation of resources matter for the impact of state taxes on business activity.

The remainder of this paper is organized as follows. Section 3.2 discusses the data, empirical strategy and main results. Section 3.3 discusses the theoretical models we use to understand the empirical results. Section 3.4 concludes.

3.2 Empirical Findings

Our state-level estimation is based on two datasets: a quarterly state-level macro dataset estimated using the mixed-frequency VAR approach developed by Schorfheide and Song (2015), and narrative federal personal and corporate income tax shocks à la Mertens and Ravn (2013), which in turn is based on Romer and Romer (2010). To identify the state-specific dynamic effects of federal tax changes, we follow closely the estimation and identification strategy of Mertens and Ravn (2013).

3.2.1 A Quarterly State-level Macro Dataset

Most of the postwar macro data in U.S. are available at the quarterly frequency or higher. This makes it convenient for macroeconomists to study the aggregate economy using national-level data. However, most state-level macro data are either missing, incomplete, or only available at the annual frequency. For example, capital and investment data are not readily available from any public source; personal consumption expenditure (PCE) is only available in BEA Regional Accounts since 1997; and there's no quarterly GDP data until 2005. Table 9 displays our collection of the main state-level variables, together with their sample period, frequency, source and additional notes.[1] Our sample period is 1963-2017. All the quarterly or monthly series, if necessary, have been seasonally adjusted using the Census X-13ARIMA-SEATS seasonal adjustment program. Nominal GDP and consumption data are transformed to their real counterparts in chained 2009 million dollars. More details for data construction are relegated to Appendix B.1.1.

To estimate a balanced panel of quarterly state-level dataset, we employ the mixed-frequency VAR estimation methods in Schorfheide and Song (2015), in which the main purpose is to compare the forecast performance of a standard quarterly-frequency VAR with that of a mixed-frequency one, and the estimated monthly historical series are their by-products. We analogously infer the quarterly components of the annual observations to construct a balanced state-level time series, but depart from their approach in the following ways. First, our framework is more flexible in allowing for the change in observation frequency (e.g. GDP and Tax Revenue), as well as missing observations (e.g. Unemployment Rate before 1976). Second, in addition to the state data, we add their national counterparts and financial variables (Treasury Bond Yield, Fed Funds Rate, and Corporate Bond Yield) as separate "national block" regressors. Table 14 in Appendix B.1.1 lists all the variables included in the national block.

[1] Since there's much shorter sample for consumption and the estimated data is sensitive to the choice of initial distribution in the Bayesian estimation, we remove this variable from our estimation sample in this paper.

Table 9: List of State-level Macro Variables in the Estimation Sample

Variable Name	**Span and Frequency**	**Source**	**Notes**
Personal Income	1948 – , Q	BEA	nominal
Total Nonfarm Employment	1939 – , M	BLS	seasonally unadjusted before 1990
GDP	1963 – 2005, A; 2005 – , Q	BEA	1963 – 1987: nominal, 1972 SIC; 1987 – 1997: 1987 SIC; 1997 – : 2007 NAICS
Government Expenditure	1951 – 2016, A	Census	nominal
Capital	1963 - 2016, A	McMurry and Williams (2018)	
State Tax Collection	1951 – 1993, A; 1994 – 2017, Q	Census	1951 – 1993: nominal; 1994 – 2017: nominal, seasonally unadjusted
Unemployment Rate	1976 – , M	BLS	
PCE	1997 – 2016, A	BEA	nominal
CPI	1950-2017	extension of Herkenhoff, Ohanian and Prescott (2018)	

In particular, we assume that each state economy evolves at quarterly frequency according to the following *state-transition equation*:

$$x_t = \sum_{i=1}^{p} \Phi_i^s x_{t-i} + \sum_{j=0}^{q} \Phi_j^n y_{t-j} + \Phi^c + u_t, u_t \sim i.i.d.N(0, \Sigma)$$

where x_t is a $n \times 1$ vector of state macro variables that contains n_a variables observed at the annual frequency (log real GDP, log state government expenditure, log real capital, log state tax revenue, log CPI) and n_q variables observed at the quarterly frequency (log personal income, log total non-farm employment, and unemployment rate); y_t is a vector of national variables that is assumed to be exogenous to the state economy; Φ_i^s and Φ_j^n are the coefficients on lagged state and national variables respectively; Φ^c is a vector of constants; p and q are the lags included in state and national variables; the error vector u_t is assumed to be *i.i.d.* and follow a multivariate normal distribution. Based on some preliminary exploration of the marginal data density, we set the number of lags in the quarterly state transition of the mixed-frequency VAR to 4 and assume no lags in the national block so that the state economy is only affected by contemporaneous national economic conditions.

The *measurement equation* of the state-space representation is imposed in a way that annual observations are equal to the average of their quarterly latent components for the five variables that are observed at the annual frequency in x_t. In the Bayesian estimation stage, we assume the Minnesota prior distribution for (Φ, Σ), where $\Phi = (\Phi_1^s, ..., \Phi_4^s, \Phi_0^n, \Phi^c)$; compute the conditional posterior distribution of latent variables and estimation parameters using the standard Kalman filter; Gibbs sample over the two conditional posterior densities; and take the median of the latent variable distribution as our estimates for the quarterly components of the n_a annually-observed variables. Since this paper mainly focuses on the state-level impact of federal tax shocks, we don't fully describe the estimation process here. A companion paper Liu and Williams (2018) has a detailed account of the state-space formulation, prior distribution assumption, hyperparameter selection, initial sample distribution etc. for the updated mixed-frequency

VAR model. Curious readers may also refer to Schorfheide and Song (2015) who lay the foundation of our main strategy.

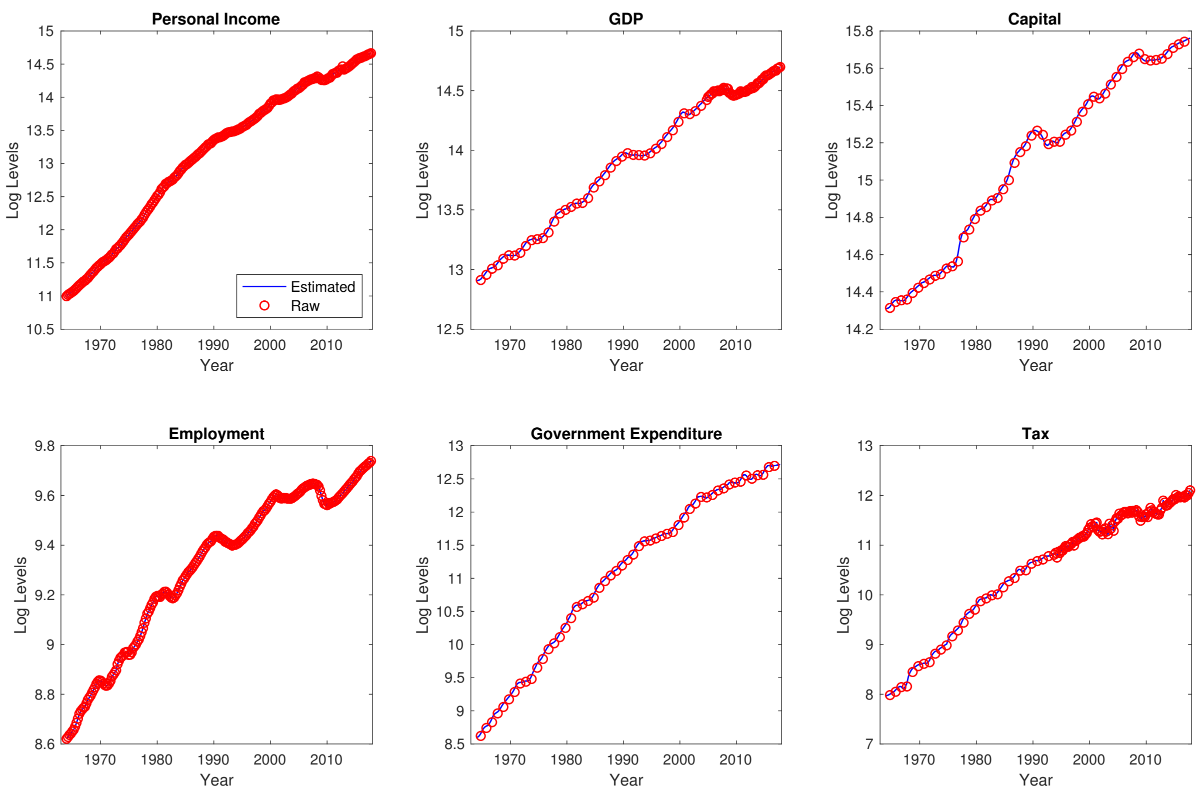
Figure 15 shows the estimated (blue line) against raw (red circle) series of some key variables in an example state, California. Table 10 provides summary statistics of some key variables in our sample. For the key economic indicators like personal income, GDP and employment growth, we consistently observe cross-state heterogeneity in the mean growth rates, cross-time standard deviation of growth rates, and the correlation between state-level and aggregate growth. For instance, the average U.S. GDP growth in our sample period is 2.88%, but the state-level GDP growth ranges from 1.64% to 4.53%, indicating even bigger long-run growth gaps. Standard deviation of state-level growth also tends to be widely dispersed, and for most of the states, output growth is on average more volatile than the U.S. as a whole, indicating a cross-state smoothing effect of growth volatility. The correlations between state-level and aggregate output growth are on average low, and widely dispersed across states too.

In sum, there's substantial cross-state heterogeneity in our state-level macro dataset, and the state-level data are only weakly correlated with their aggregate counterparts, both of which point to the necessity to go beyond the aggregate data to study the policy impacts. In this paper, we explore this vein in a particular setting: the impact of federal tax policy changes.

3.2.2 Narrative Federal Personal and Corporate Income Tax Shocks

Mertens and Ravn (2013) document the exogenous narrative exogenous federal tax changes for personal and corporate income ΔT_t^{PI} and ΔT_t^{CI}, calculated by the legislated tax liability changes in individual income and employment taxes over personal taxable income of the previous period, and the legislated changes in corporate income tax liability over corporate profits of the previous period. Motivated by the narrative

Figure 15: Quarterly Data Estimates: California



Notes: plotted period: 1964 – 2017; frequency: quarterly.

Table 10: Summary Statistics of Key Variables

	U.S.	10th State	Median State	40th State
			Real Personal Income	
Mean Growth (%)	3.08	2.33	2.84	3.46
S.D. Growth (%)	3.23	3.76	4.46	5.48
Corr. with U.S.	1	0.52	0.64	0.72
			Real GDP	
Mean Growth (%)	2.88	2.29	2.91	3.58
S.D. Growth (%)	3.24	3.62	4.16	5.50
Corr. with U.S.	1	0.31	0.53	0.64
			Employment	
Mean Growth (%)	1.75	1.22	1.89	2.30
S.D. Growth (%)	2.14	2.57	2.90	3.38
Corr. with U.S.	1	0.64	0.76	0.85
			Price Index	
Mean Growth (%)	3.87	3.59	3.67	3.69
S.D. Growth (%)	3.07	2.36	2.40	2.49
Corr. with U.S.	1	0.78	0.81	0.84

Notes: sample period: 1964Q1-2017Q4. We compute the U.S. real personal income, real GDP, employment, and price growth using U.S. quarterly aggregate data; and the state-level growth using our estimated state quarterly growth data. We separately rank each summary statistic by state, and report that of the 10th, median and 40th state. So the values in each column (except for column "U.S.") may correspond to different states.

approach of Romer and Romer (2010), they include only the "exogenous" tax changes in this sample, including those motivated by long-run growth prospects and those made to deal with an inherited budget deficit not related to current economic conditions or spending changes; exclude the "endogenous" ones like countercyclical policy changes and spending-driven changes made to counteract the government spending. We extend their dataset up to 2017. In particular, we add two personal income tax changes (the Tax Relief, Unemployment Insurance Reauthorization and Job Creation Act of 2010, and the American Taxpayer Relief Act of 2012) and one corporate income tax change (the American Taxpayer Relief Act of 2012), following the rules of picking "exogenous" tax shocks and the additional rules in separating personal and corporate income tax shocks, as in Mertens and Ravn (2013). Details about this process can be found in Appendix B.1.2.

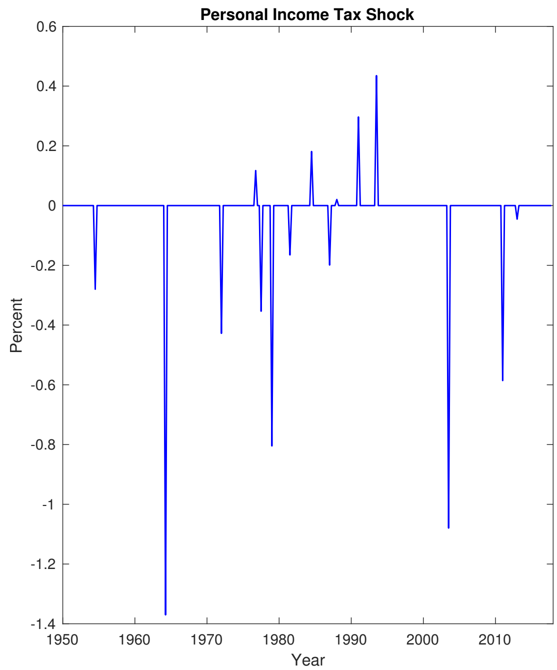
Our extended sample of narrative shocks for the period 1950Q1 – 2017Q4 is plotted in Figure 16. In identifying the effects of these tax shocks with the state level macro data, we use the subsample period 1964 Q1 – 2017Q4, which covers nearly all of the noted tax changes.

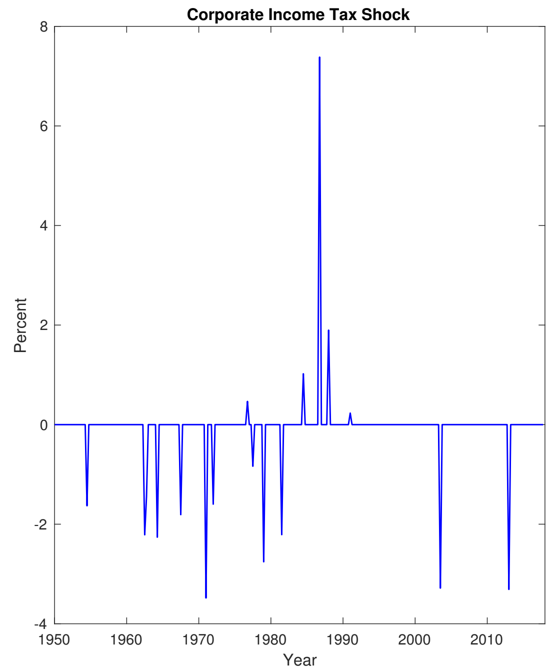
3.2.3 Main Estimation

With the state-level macro datasets, and narrative accounts of tax policy changes at the federal level, we proceed with our main questions: what are the state-level responses of federal tax policy shocks? Is there heterogeneity in those responses? What account for the differences?

To contrast the state-level responses with the aggregate ones, we follow closely the estimation strategy of Mertens and Ravn (2013): to exploit the information of narrative measures of tax changes for identification in a SVAR framework. We impose the same identification restriction that our narrative tax policy shocks are only correlated with the structural tax shocks, but not other macro shocks, which is even more validated in

Figure 16: Narrative Shocks: 1950Q1 – 2017Q4





our setting if one considers each state as a small open economy. Besides, it's important to control for changes in the other tax rate when analyzing the effects of a shock to one tax rate change, since in our constructed sample personal and corporate tax changes are positively correlated. Same as in Mertens and Ravn (2013), we impose a parametric recursivity assumption of the relationship between reduced-form VAR residuals and structural shocks.

However, due to data limitations, our sample period (1964Q1 – 2017Q4) is different from theirs (1950Q1 – 2006Q4), and our state-level macro variables are not adjusted for state population. To make more sensible comparisons, we replicate their results using our sample period and aggregate macro data without adjusting for nationwide population. We show that across a wide variety of specifications, the main result still holds, that is, short-run output effects of tax shocks are large.[2] This is not surprising

[2]See Figure 29 in Appendix B.2.

given that various studies have confirmed this result.

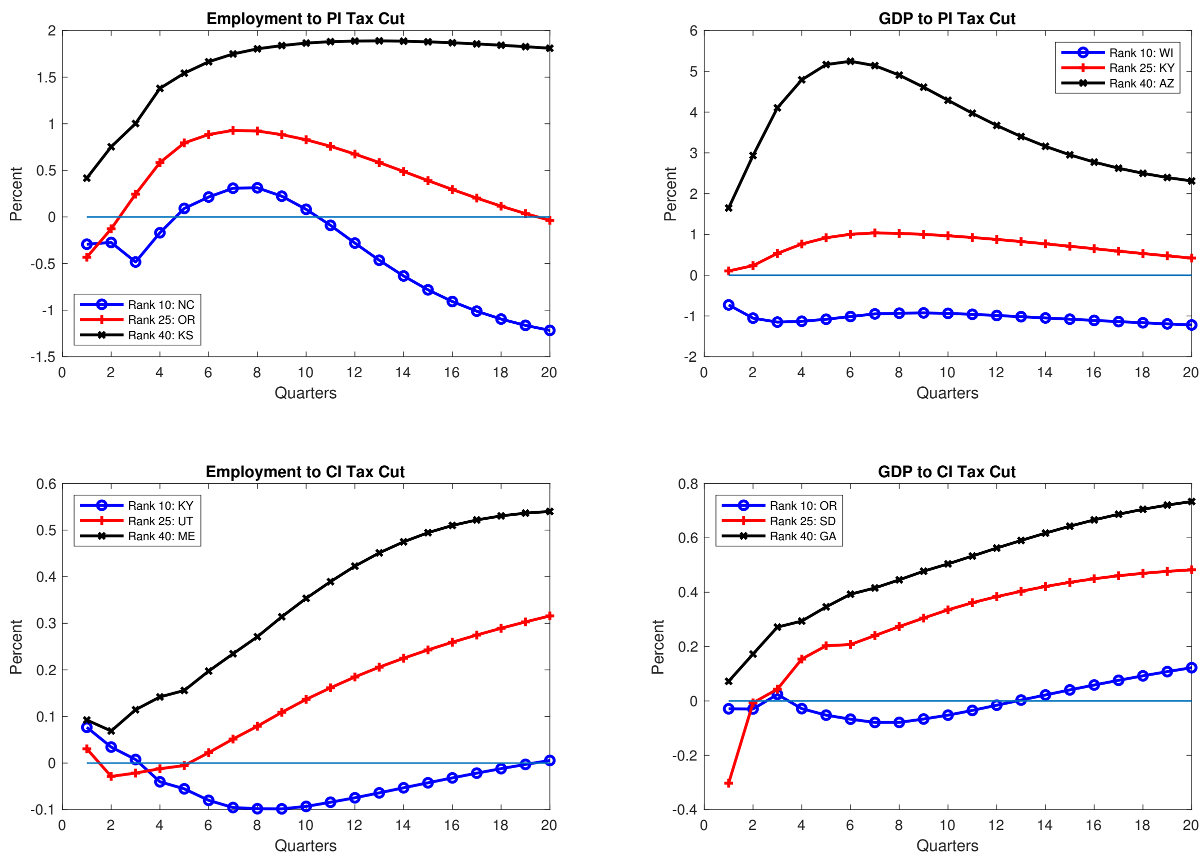
We estimate a SVAR for each state. In our benchmark analysis, four variables enter the proxy SVAR: average personal income tax rate (APITR), measured by (personal current taxes + contributions for government social insurance)/personal taxable income; average corporate income tax rate (ACITR), measured by taxes on corporate profits/corporate profits; logarithm employment; and logarithm real GDP. As the fiscal variables are the same across all the state-level regressions, this setting is in line with our main question, that is, the heterogeneous impacts of common shocks at the federal level. Our estimation sample covers the period 1964Q1 – 2017Q4, and the autoregressive lags are set to 4.

In each regression, we calculate the dynamic impulse responses of employment and GDP to a –1% federal personal and corporate income tax shock. For each response function, we rank by state the cumulative responses over a 20-quarter horizon. In the main text–for exposition purposes–we report the point estimates for only the 10th, 25th and 40th states, as shown in Figure 17, with the full results being relegated to Appendix B.2 Figure 30. As the results for Alaska and Wyoming are clearly outliers for almost every result (benchmark and various robustness checks), they are not included in these graphs.

A –1% federal personal income tax shock leads to expansions of employment and GDP for most states (most of the impulse responses are above the x-axis). In these states, the peak responses of employment range from slightly lower than 1% up to 5%; and those of GDP range from 1% to 7%. Similarly, there are expansionary output and employment effects of corporate tax cut for most states, albeit the magnitudes of these responses are on average lower: from slightly above 0 to 1.5%. In a few states, the effect of tax cuts seems to be contractionary, but in the following analysis we show that most of these negative responses are in fact not significantly different from 0.

Our analysis wouldn't be complete without discussion on the significance of these responses. We compute the 95% confidence intervals for each state-level estimation using

Figure 17: Benchmark Impulse Responses: 10th, 25th and 40th States Ranked by Cumulative Responses



Notes: The top two figures show the impulse responses of employment and GDP to a -1% shock to the average federal personal income tax rate, where APITR is ordered second in the SVAR; the bottom two figures show the impulse responses of employment and GDP to a -1% shock to the average federal corporate income tax rate, where ACITR is ordered second in the SVAR. States are ranked by their cumulative impulse responses over a 20-quarter horizon. The 10th, 25th and 40th states in each ranking are displayed here.

the recursive wild bootstrap with 10,000 replications[3], and replace the point estimate with 0 if it isn't significantly different from 0 at the 95% level. Though not perfect, we believe this measure generates conservative estimates of the actual effects of tax policy changes. Figure 18 shows the impulse responses when we take into account the significance of an estimate. For both personal and corporate income tax changes, there are 1-3 states that respond quite differently from the rest: expansionary tax changes are contractionary in these states. Since the number of these states are small, in this paper we do not specifically investigate why these states respond so differently, but focus on the rest of the sample.

Our result shows that more than a half of the states do not respond significantly to either personal or corporate income tax change at any point within the 20-quarter horizon. A small subset of them respond to neither. For the states that do respond to either tax cut, the responses of employment and GDP are almost always positive, although the magnitude and persistence of these effects are quite heterogeneous too. Compared with corporate income tax, the magnitude of impact (if there's any) on personal income tax change is bigger, but fewer states have significant responses. Given that we use the same methods, our result is in clear contrast with but not necessarily contradicts the conclusions in previous literature drawn with national-level macro data; it indicates that the significant positive response of output (and others) that they find at the aggregate level might have been driven by just a few states, while the rest do not respond to these policy changes at all.

Similarly, we calculate and rank the cumulative responses adjusted for significance over a 20-quarter horizon. For the minimum and maximum responding states (among

[3]We follow the confidence interval inference method in Mertens and Ravn (2013) to make our state-level results comparable to theirs from nationwide data, and to highlight the heterogeneous policy effect. However, it has been brought to our attention that there's recently a debate on the validity of their chosen inference method (Jentsch and Lunsford, 2018). In a reply paper, Mertens and Ravn (2018) conclude that "Our results show that the conclusions about the economic and statistical significance of the macroeconomic effects of tax changes in Mertens and Ravn (2013) remain broadly valid".

those that have non-zero cumulative responses), we report in Figure 19 the point estimates and their 95% confidence interval bands. Take the GDP response to corporate income tax cut as an example; there seems to be only a short-lived on-impact significant effect for Illinois, while for Rhode Island the responses are on average both much stronger and long-lasting.

3.2.4 What Accounts for the Differences?

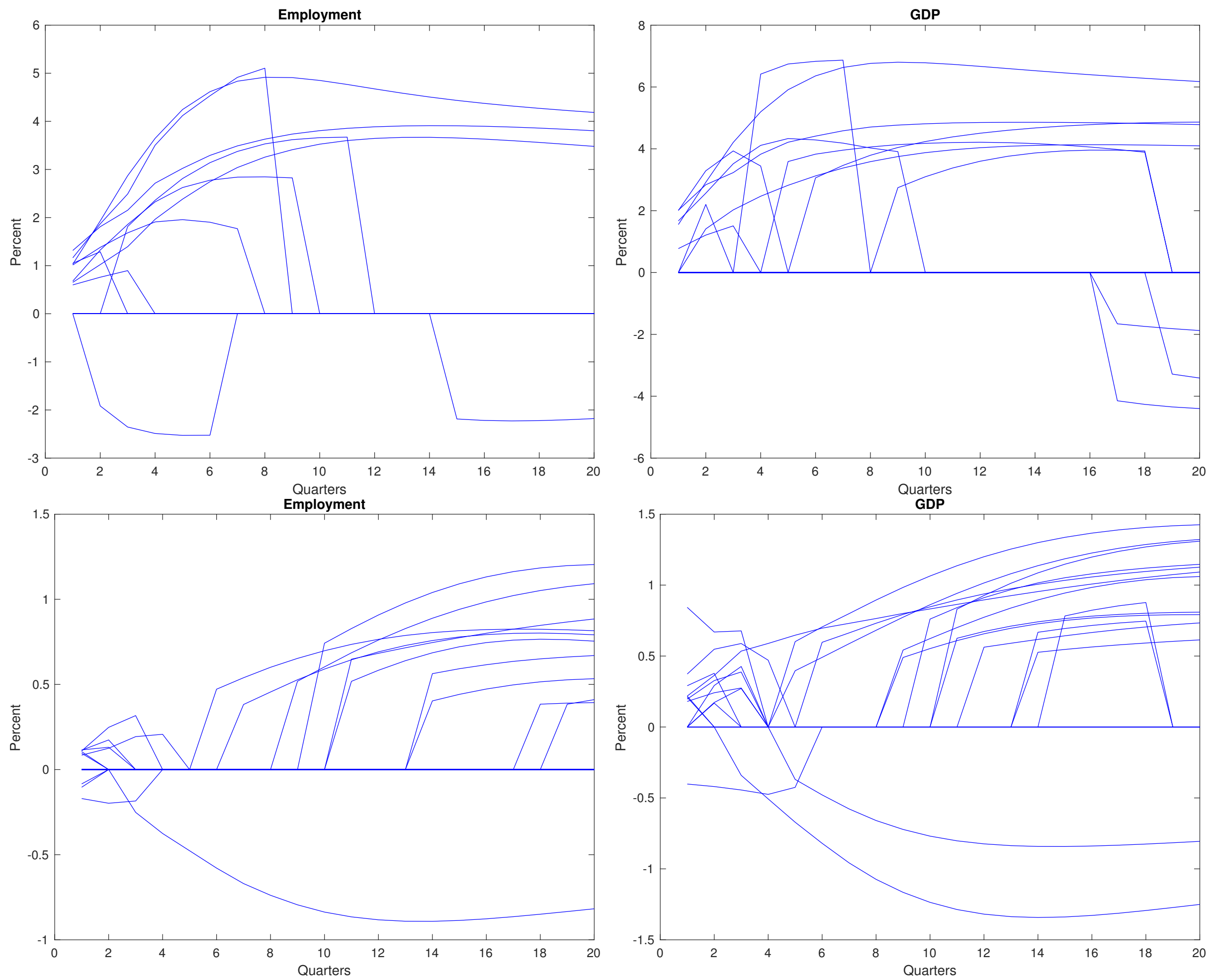
Given the heterogeneous state-level responses of federal tax shocks, a natural question that follows is: what drives the heterogeneity? While we are not able to exhaust the possible candidates, we investigate in this paper two most likely ones: state tax and economic structure summarized by capital share of state income. Our state-level capital share series come from the calculation by McMurry and Williams (2018) [4]; average state individual income tax rate is from NBER TAXSIM; average state corporate income tax rate is from the calculation by Suárez Serrato and Zidar (2016); sales tax rate is from the Book of States. The average state tax rates and capital share of income are summarized in Table 15 in Appendix B.2.

As is evident from this table, state tax rates and capital share of income both vary considerably across states. In fact, for each tax category there are at least five states that don't collect it at all over the past decades; and among those that do collect, tax rates vary a lot. So does the capital share of income.

Tax policies at the federal level potentially have different effects on different states, depending on their economic and fiscal structures. A corporate tax cut, for example, would disproportionately boost states with different factor intensities. Meanwhile, we notice that both tax rates and tax bases vary considerably across states: sales, individual income and corporate income tax rates are widely dispersed across states. The

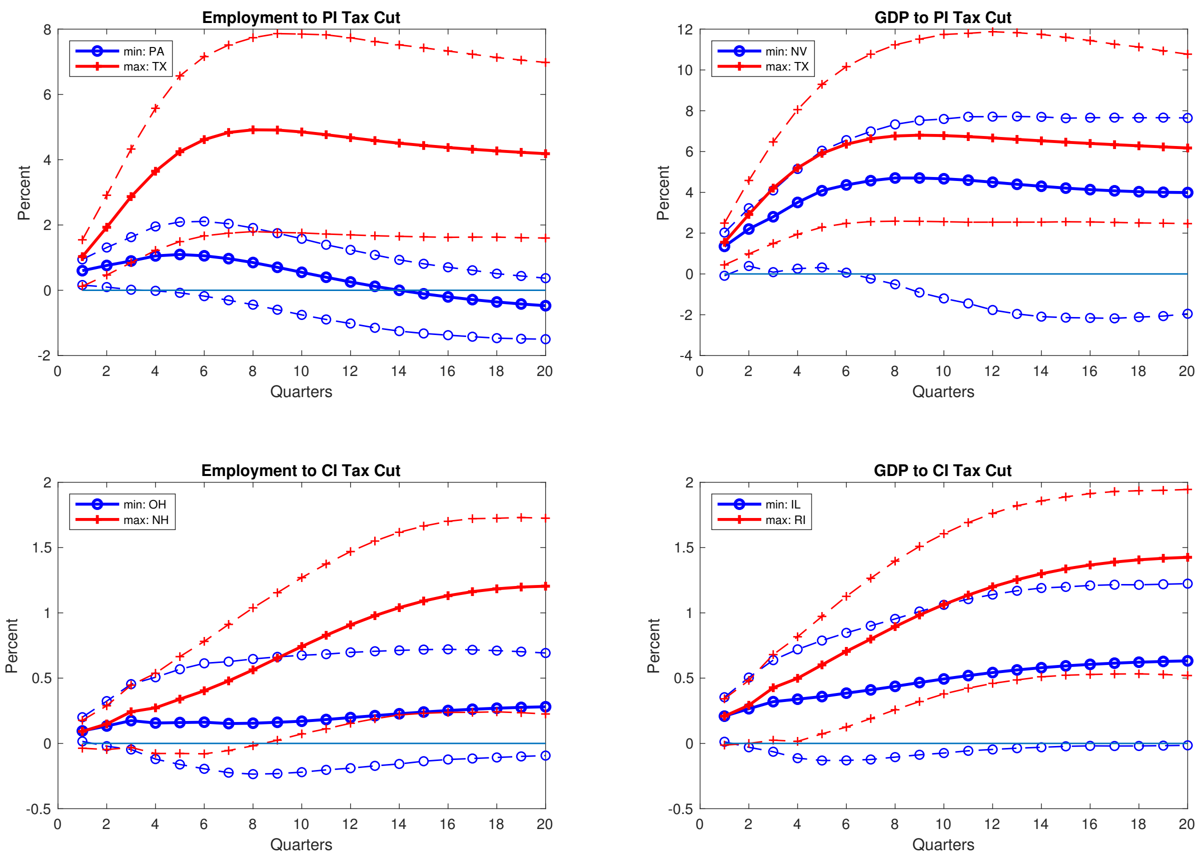
[4] In McMurry and Williams (2018), capital share of income at the state level is calculated by $\alpha_{it} = \frac{R_{it}K_{it}}{P_{it}Y_{it}}$, the numerator being payments to capital measured by GOS of state i and the denominator being the nominal GDP of state i, both available in the BEA.

Figure 18: Impulse Responses: Benchmark (insignificance set to 0)



Notes: In this figure, if 0 lies within the 95% confidence interval of the impulse response of a given variable at a given time, it is set to 0. The top two figures show the impulse responses of employment and GDP to a -1% shock to the average federal personal income tax rate, where APITR is ordered second in the SVAR; the bottom two figures show the impulse responses of employment and GDP to a -1% shock to the average federal corporate income tax rate, where ACITR is ordered second in the SVAR.

Figure 19: Benchmark Impulse Responses: Min and Max States Ranked by Cumulative Responses



Notes: The top two figures show the impulse responses (solid lines), together with the 95% confidence intervals (dashed lines) of employment and GDP to a -1% shock to the average federal personal income tax rate, where APITR is ordered second in the SVAR; the bottom two figures show those to a -1% shock to the average federal corporate income tax rate, where ACITR is ordered second in the SVAR. Since the impulse responses are insignificant over the 20-quarter horizon for more than half of the states, we report only the minimum and maximum responding states, ranked by the cumulative impulse responses where–unlike the previous graph–insignificant ones are replaced by 0.

interaction between state and federal tax is likely to be one of the driving forces behind the heterogeneity in federal tax impacts across states.

We measure the overall tax response by summing up the responses over a horizon of 20 quarters by state, both ignoring and considering whether they are statistically significant. This measure of response could be interpreted as the cumulative tax effect over a horizon of 20 quarters, so we are not distinguishing between short and long-run impacts. In the next subsection we show that the statistical significance concern does not affect our result. Using peak response is not likely to change our results either since we observe that a state that has a high peak response also tends to have a big cumulative response.

In Figure 20, we plot the cumulative employment and GDP responses to a –1% personal and corporate income tax shock, against the average capital share of each state. Same as the results shown in Figure 18, the responses to personal income tax shock are either small or not significantly different from 0 for most states; corporate income tax cut leads to rises in employment and GDP for a larger number of states.

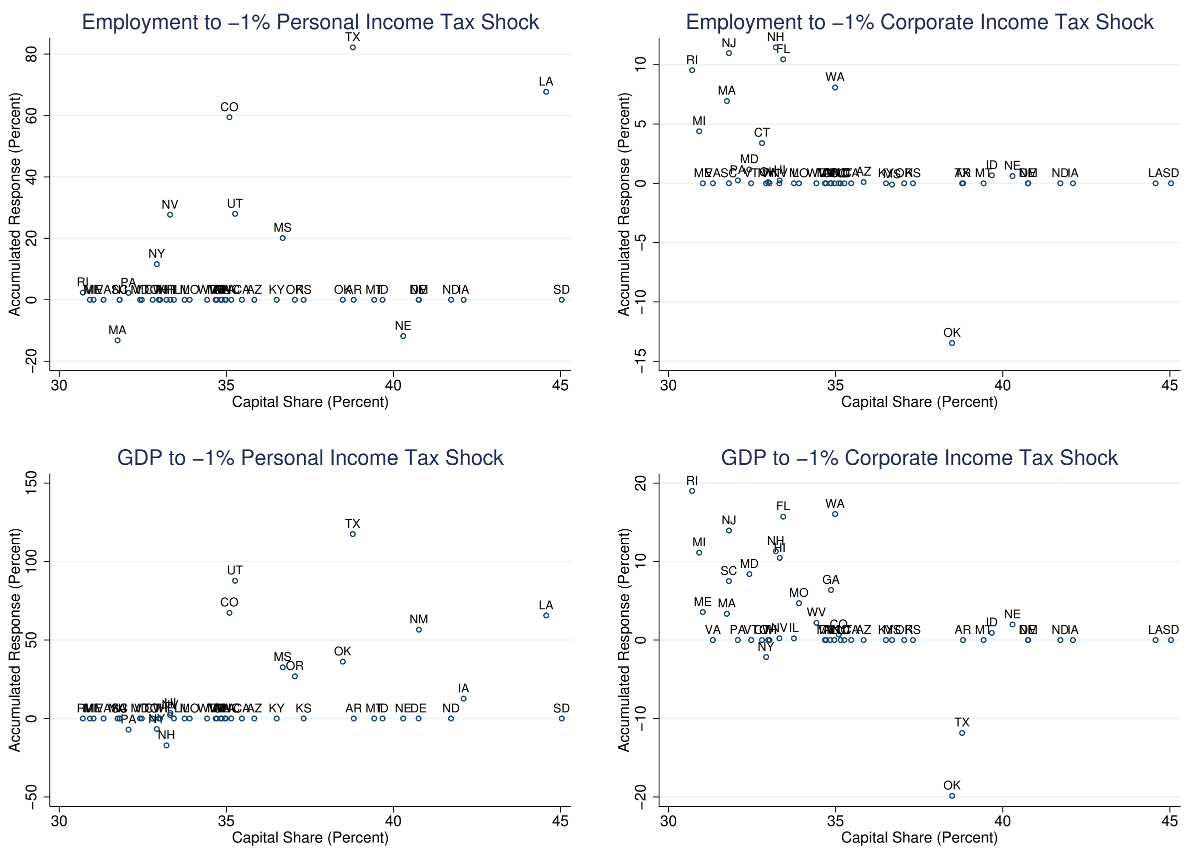
From Figure 20, we find that although the employment and output effects of a corporate tax cut are significant for only around half of the states, these states tend to feature *smaller* capital share. While for the states that have relatively high capital share, the responses are almost always not significant. Big output response to a personal income tax cut, however, tends to happen only to higher capital share states, but the relationship between capital share and employment response to personal income tax cut is unclear.

We test the above results controlling for the potential effects of state tax structure, and analyze the effect of capital share on tax responses in the following cross-sectional regression model:

$$r_i = \boldsymbol{\beta} \boldsymbol{X_i'} + \varepsilon_i \tag{3.1}$$

where r_i denotes the cumulative response of state i; $\boldsymbol{X_i}$ is a 1×5 vector that contains

Figure 20: Cumulative Response by State (sorted by capital share)



a constant 1, capital share, average state individual income tax rate, average state corporate income tax rate, and sales tax rate; $\boldsymbol{\beta}$ is the coefficient vector that is reported in Table 11 Panel A (the full sample of states) and B (Alaska and Wyoming excluded). Panel C reports the result when the three tax rates are replaced with each type of tax revenue as a fraction of total revenue, an ex-post measure of the state tax structure.

Across the three sets of regressions, the correlations between capital share and the output response to both federal corporate and personal income tax cut are significant. In particular, a 1% higher capital share is associated with 0.7% to 0.9% lower output response to corporate income tax cut and 2% – 3% higher output response to personal income tax cut. Capital share is also significantly associated with lower employment response to corporate tax cut, but the impact is relatively smaller. In Appendix B.2 Table 16, we show that our result is robust if we construct the cumulative responses using only point estimates (without considering statistical significance).

We do find strong and robust negative correlation between average state personal income tax rate and the employment response to corporate tax cut: a state with lower average state personal income tax rate tends to have higher employment response to a federal corporate tax cut. However, unlike capital share, the variation in state tax structure doesn't seem to be an important and robust factor in explaining most of the heterogeneous responses of federal tax changes. This result is consistent with our finding in various model simulations with both state and federal taxes present.

Table 11: Cumulative Responses on State Characteristics

	Panel A: All States				Panel B: Benchmark				Panel C: Using Tax Ratios			
	EMP-PIT	GDP-PIT	EMP-CIT	GDP-CIT	EMP-PIT	GDP-PIT	EMP-CIT	GDP-CI	EMP-PIT	GDP-PIT	EMP-CIT	GDP-CI
State PITR	-1.054	-6.611	-1.625***	0.574	-1.649	3.613	-1.900***	-1.391				
	(1.501)	(8.470)	(0.580)	(1.818)	(1.826)	(3.211)	(0.569)	(0.930)				
State CITR	-1.733	-1.090	0.274	-0.329	-2.036	-3.546*	0.380*	0.188				
	(1.207)	(2.989)	(0.187)	(0.585)	(1.320)	(2.010)	(0.207)	(0.424)				
Sales TR	0.579	-4.105	-0.172	0.905	0.437	1.746	-0.347	-0.239				
	(0.973)	(5.407)	(0.302)	(1.113)	(1.024)	(1.677)	(0.260)	(0.349)				
Capital Share	0.659	3.128**	-0.476***	-0.893***	1.058	2.681**	-0.497***	-0.845***	0.573	1.914*	-0.374***	-0.696***
	(0.980)	(1.371)	(0.133)	(0.307)	(1.079)	(1.228)	(0.135)	(0.228)	(0.979)	(1.038)	(0.116)	(0.210)
PIT/T									-0.311	-0.00399	-0.104***	-0.0456
									(0.286)	(0.436)	(0.0385)	(0.0803)
CIT/T									-2.020	-3.079	0.503**	0.538
									(1.244)	(1.847)	(0.221)	(0.425)
Sales/T									-0.259	-0.124	0.0114	0.121
									(0.259)	(0.418)	(0.0516)	(0.0977)
Constant	-6.412	-57.74	20.66***	30.43**	-15.93	-76.87*	22.11***	35.18***	14.22	-35.12	13.79**	21.10*
	(37.80)	(62.87)	(5.957)	(14.98)	(37.89)	(41.56)	(5.569)	(8.674)	(43.70)	(56.28)	(5.701)	(11.11)
N	50	50	50	50	48	48	48	48	48	48	48	48
adj. R^2	0.066	0.222	0.234	0.209	0.122	0.153	0.259	0.148	0.083	0.142	0.283	0.192

standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Since corporate tax cuts only affect the corporate sector, consisting mainly of C corporations, one may be concerned that the measured state capital share may be correlated with the relative size of the corporate sector, which trivializes our result. To examine this possibility, we analyze relevant tax statements from the Internal Revenue Service (IRS), and present in Figure 21 the scatter plot of non-corporate sector share against capital share for the year of 2010 [5]. While the (non)corporate share varies widely across states, its correlation with state capital share is close to 0 (0.02 for year 2010), indicating that while sectoral share itself may be an important factor driving the difference in tax responses, it's not the entire story.

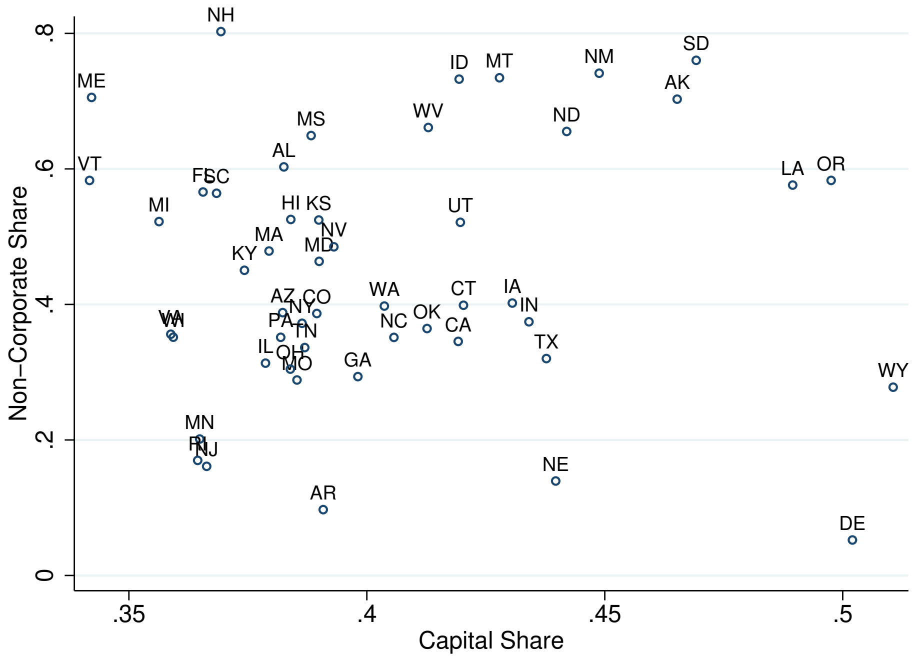
3.2.5 Robustness

In addition to the benchmark, we also explore several alternative specifications in our state-by-state SVAR framework. One may be concerned that our estimated state data may involve measurement errors. We report in Figure 31 and 32 the estimation result where only personal income and employment is in the SVAR. Both of them are available at quarterly frequency, so there are no measurement errors coming from the mixed-frequency VAR estimation. Still, there are big cross-state heterogeneity in employment and personal income responses to tax cuts.

In the benchmark estimation of Mertens and Ravn (2013), regression specification seems important for the quantitative results (but not qualitatively). For example, the output response to personal income tax cut is smaller and less persistent when federal

[5] Non-corporate sector share is defined as the non-corporate sector business income over total business income, which includes both corporate and non-corporate ones. We obtain the information on non-corporate (sole proprietorship, S corporation and partnership) business income from the IRS "Individual Income and Tax Data, by State and Size of Adjusted Gross Income"; corporate income tax revenue by state from "IRS Collections by State and Type 1998-2016"; and calculate the average corporate income tax rate from IRS "Returns of Active Corporations - Table 1". Assume that the corporate tax rate is the same across states, corporate sector business income, not directly available from IRS by state, is then calculated as the corporate income tax over average corporate tax rate (around 22% for 2010). Since Partnership/S-corp business income cannot be separately identified from the Adjusted Gross Income prior to 2009, we calculate the correlation between (non)corporate sector share and capital share for each year after 2009, and report here that of 2010. The low correlation result applies to other years.

Figure 21: Non-Corporate Sector Share v.s. Capital Share, 2010



government debt is removed from their estimation sample. Figure 33 plots the cumulative response of each state against its average state capital share, where we add state government expenditure to the benchmark SVAR framework. The relationship between responses to personal income tax shock and capital share is much weaker; but our main result on the effect of corporate income tax cut is quite robust: states that have bigger responses to corporate income tax cut tend to have lower capital share of income.

The relationship between corporate tax responses and state capital share is also robust when we calculate the cumulative tax response using the point estimates without regard to whether it's statistically significant at the 95% confidence level, as is illustrated in Table 16. In fact, the average across-state difference in the cumulative response of either employment or GDP to corporate income tax cut is even more pronounced for every 1% difference in the state capital share.

We also add three nationwide variables to the benchmark analysis: GDP, Government Spending and Debt, all in log real terms. By this, we single out the fiscal policy impacts by controlling for the aggregate economic conditions. Still, we find substantial heterogeneity of state-level responses to federal tax changes. The negative relationship between average capital share and output response to the corporate income tax cut still holds. However, there are more states with significantly negative employment responses to corporate income tax cut, a result that is puzzling but seemingly consistent with the finding in Mertens and Ravn (2013) that "changes in corporate taxes have much less pronounced effects on the labor market" drawn using nationwide data.

3.2.6 Summary of the Empirical Results

We analyze the state-level implications of federal personal and corporate income tax changes using our own constructed state-level quarterly macro dataset, and an extended sample of federal narrative tax shocks. In contrast to the past findings of strong and significant expansionary effects of both tax cuts at the aggregate level, we find that more than half of the U.S. states are (statistically) unresponsive to either tax cut, and a few states respond to neither. We also find robust evidence that a state with higher capital share of income tends to have smaller output and employment responses to the federal corporate tax cut, while those responding the most to corporate tax cuts are almost always states with low capital share.

3.3 Modeling Impacts of Tax Changes

We now turn to some economic models to help understand our empirical results. We focus on our most robust empirical finding, that states with a lower capital's share of income have larger output responses to reductions in the federal corporate tax. This is also the most surprising result, as it is difficult to rationalize this pattern of response in a standard one-sector model. Across many settings, the cumulative impact of a capital tax shock on output is larger when the capital share is larger. However the size of effect on impact of the tax shock may be larger when the capital share is smaller, and reallocation of resources across state borders in response to the tax cut may increase this difference. This emphasis on reallocation leads us to study the reallocation of resources across sectors. We show that a two-sector model, with corporate and non-corporate sectors, can explain (at least qualitatively) the larger output response with a smaller capital's share. Barro and Furman (2018) consider a similar two-sector model in their evaluation of the 2017 federal tax reform. The key to establishing our result is that the larger overall capital's share in a state must result from a disproportionate increase in the non-corporate sector.

While we do not focus on it here, most models also suggest that the impact of changes in federal taxes should depend on state tax rates. For example, states that have a high tax rate on one income source of income compound the distortions associated with federal tax rates on that income source. Thus in a high state-tax state, a cut in federal taxes will result in a proportionately larger reduction in distortions, which would translate into larger impacts on outcomes. However we find relatively little empirical evidence in support of these results. Instead, Table 3 presents some evidence that *lower* state personal income tax rates are associated with *larger* effects of federal corporate tax cuts. This pattern of cross-factor tax dependence is also surprising.

3.3.1 One-Sector Models

In a standard one-sector neoclassical growth model, it is common to assume that all production takes place in the corporate sector. In this case, assuming no pure profits in equilibrium and that investment is financed by equity, the corporate tax acts just like a tax on capital income. We show that in sector models corporate tax cuts have larger long run and cumulative output responses in more capital-intensive economies. This result is driven by the larger tax base to which the tax is applied, and this effect dominates other aspects of most models which may impact the short-run responses, such as labor force dynamics and various frictions. Multi-region models, which more explicitly model trade and have been used to study cross-state dynamics in the US, may also lead to enhanced impact responses due to factor reallocation. But it is difficult to rationalize our observed empirical result of a larger cumulative response to a corporate tax cut with a lower capital intensity.

The intuition for the relation between capital intensity and the output response to a corporate tax cut can be seen in a simple modification of the traditional Harberger (1962) analysis of the incidence of the corporate tax. In particular, consider a competitive firm with a standard Cobb-Douglas production function with capital share α facing a corporate tax of τ, and for simplicity assume that there are no depreciation deductions. Then the standard optimality conditions will lead to:

$$\begin{aligned}(1-\tau)\alpha(K/N)^{\alpha-1} &= R \\ (1-\alpha)(K/N)^{\alpha} &= w,\end{aligned}$$

with R being the interest rate and w the real wage. Thus if we use lower case letters to denote percent (log) deviations following a change in the tax, we have approximately:

$$k - n = -\frac{1}{1-\alpha}(r+\tau),$$

which in turn implies:

$$y = n - \frac{\alpha}{1-\alpha}(r+\tau)$$

In the simple case of a small open economy, r is determined in the world market. Most US states are small relative to the whole country, and thus do not have much influence over national interest rates. Nonetheless, we would expect that changes in federal tax rates which affect all states would lead changes in the US interest rate. Ignoring this aspect for now, it is clear that the assumptions on factor supplies and mobility affect the magnitude of the change in output in response to a change in the tax. If labor is immobile and in elastic supply, as in Harberger's long run analysis, then the output response is solely due to changes in capital:

$$y = -\frac{\alpha}{1-\alpha}\tau.$$

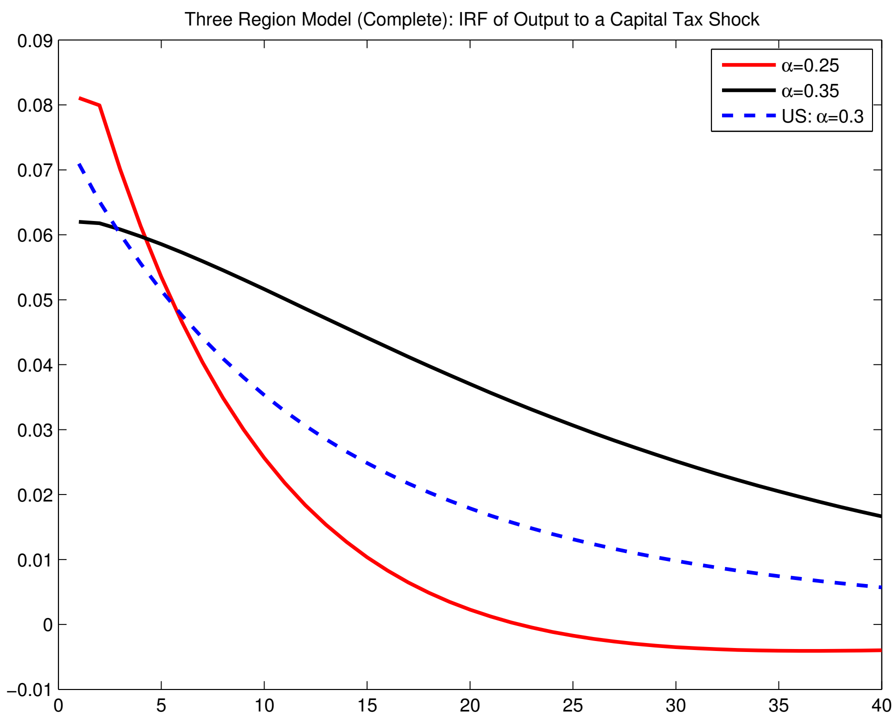
Thus a cut in the corporate tax rate τ will have a larger effect in more capital-intensive economies with larger α. On the other hand if capital were immobile and labor free to adjust, then output would increase in an amount equal to the tax cut $y = -\tau$.

The same basic forces in the traditional static incidence analysis also arise in more modern dynamic general equilibrium settings. Of course one major difference is the inclusion of responses by households whose decisions on saving and employment are affected by taxation. In addition, the mobility assumptions on factors play more subtle roles as they are shifted dynamically. That is, the initial impact after an unexpected tax cut may differ from the cumulative or long-run response. This is particularly true if the model incorporates sources of real or nominal frictions or adjustment costs, which may alter the dynamic pattern of response to changes in taxes.

In the appendix, we consider a variety of one-sector models which differ in their market structure, real or nominal rigidities, and assumptions on market completeness. While the response on impact and the dynamics are affected by the details of the models, in each case we find that the cumulative response to the corporate tax cut is larger when the economy is more capital intensive. Here we provide an illustrative case. The model is a modification of a standard real business cycle model with government spending, proportional taxes on capital and labor, and lump sum taxes which ensure the government's budget is balanced. In particular, we consider a standard Cobb-Douglas production function (with varying α) and assume a representative household has additively separable preferences:

$$u(C, N) = \log C - \frac{N^{1+\eta}}{1+\eta}.$$

Figure 22: Impulse response of output to a corporate tax shock in a three region model with complete markets



We suppose that the corporate or capital income tax is time-varying and follows the standard auto-regression:

$$\tau_{t+1} = \rho\tau_t + \varepsilon_{t+1}$$

The economy consists of three regions: two states and the rest of the country. Each region has a representative consumer and representative firm, where consumer preferences are the same but capital intensities differ across regions. We suppose that each state consists of 5% of total output, with one state being more and the other being less capital intensive than the rest of the country. We also suppose that there are complete markets, so there is consumption smoothing and risk sharing across regions. The results in Figure 22 show that trade across regions alters the responses of the states to the capital tax shock, by increasing the response on impact of the less-intensive state but prolonging the impact in the more-intensive state. Thus trade and factor reallocation matter, but they suggest larger cumulative responses with more capital intensity, counter to our empirical results.

3.3.2 Two-Sector Models

As reallocation seems to play an important role in explaining our results, we now turn to a two-sector model which includes corporate and non-corporate business sectors. While in one-sector models the corporate tax is a tax on capital, it is actually a tax on the capital and profits of a particular legal form of business. As pass-through businesses comprise an increasing share of the US economy, when evaluating corporate tax changes it is important to recognize, as Barro and Furman (2018) emphasize, that many businesses do not pay this tax. Moreover, the traditional analysis of the incidence of corporate taxes, following Harberger (1962), focuses on the mobility of factors across sectors as well as states. Thus we focus on a small open economy model with the addition of a non-traded non-corporate sector, whose good (services, for example) must be supplied by domestic producers. We assume that the corporate and non-corporate sectors draw on the same supply of labor, so changes in wages are an important linkage across sectors in the response to the tax cut.

A Static Model

We begin with a version of the traditional analysis of the incidence of the corporate tax, which began with Harberger (1962), and was extended to open economies in Kotlikoff and Summers (1986), Harberger (1995), and Randolph (2006) among others. As noted above, these static analyses are best interpreted as giving the long-run response of the economy to a permanent tax change. We adapt the discussion in Randolph (2006), but we focus on output responses rather than tax incidence.

As in our discussion above, we focus on percentage deviations in response to a tax change, and we assume (as in a small open economy) that equilibrium interest rates remain unchanged. We assume that the corporate sector (with a superscript C) and non-corporate sector (with superscript N) are both competitive and have constant returns to scale production technologies with different capital intensities. The firm factor demand optimality conditions thus imply:

$$\begin{aligned} k^C - n^C &= w - \tau \\ k^N - n^N &= w, \end{aligned}$$

as only the corporate sector pays the tax, which increases its cost of capital. Both sectors earn zero profits and the corporate traded sector is the numeraire good which trades a world price, while p_N is the relative price of the domestic non-corporate good. Thus we have:

$$\begin{aligned} p^C &= \alpha_C \tau + (1 - \alpha_C) w = 0 \\ p^N &= (1 - \alpha_N) w. \end{aligned}$$

Together these imply $w = -\frac{\alpha_C}{1-\alpha_C}\tau$ and $p_N = -\frac{\alpha_C(1-\alpha_N)}{1-\alpha_C}\tau$. We suppose that the total supply of labor is fixed, which implies total changes in labor must cancel: $n_C N_C =$

$-n_N N_N$. Finally, we assume that domestic consumers have a constant price-elasticity demand function for the non-corporate good, which implies $c_N = -\varepsilon p_N$.

Combining these expressions allows us to solve for the equilibrium response of each sector to the corporate tax change. In particular, focusing on labor we get:

$$\begin{aligned} n_N &= \frac{\alpha_N \alpha_C + \varepsilon \alpha_C (1-\alpha_N)}{1-\alpha_C} \tau \\ n_C &= -\frac{\alpha_N \alpha_C + \varepsilon \alpha_C (1-\alpha_N)}{1-\alpha_C} \frac{N_N}{N_C} \tau. \end{aligned}$$

Thus in response to a cut in the corporate tax ($\tau < 0$), employment increases in the corporate sector and falls in the non-corporate sector as workers move to the sector with increased labor demand. The magnitude of this reallocation depends on the relative sizes of the sectors and their capital intensities, as well as the elasticity of demand for the non-corporate good.

In the simple special case where $\varepsilon = 1$, the analysis simplifies. In this case, labor in the non-corporate sector bears all of the response to the tax cut, with $n_N = -w$ and $k_N = 0$. Moreover, if the corporate and non-corporate sectors have equal output shares, then from their factor demand conditions, the ratio of their employment is equal to the ratio of their labor shares:

$$N_N / N_C = (1-\alpha_N)/(1-\alpha_C)$$

and therefore:

$$\begin{aligned} n_N &= \frac{\alpha_C}{1-\alpha_C} \tau \\ n_C &= -\frac{\alpha_C (1-\alpha_N)}{(1-\alpha_C)^2} \tau. \end{aligned}$$

Larger capital shares in the corporate sector α_C lead to larger employment responses in each sector and larger output responses, as in the one-sector model above. However increases in the capital share of the non-corporate sector α_N have no impact on the employment in the non-corporate sector, but lead to smaller employment responses in the corporate sector, and thus smaller output responses as well.

Intuitively, the changes in the corporate tax affect the non-corporate sector only through the effect on wages. A corporate tax cut leads to an increase in wages, and thus a reduction in non-corporate employment. For a given corporate tax cut, the percentage change in employment in the non-corporate sector is independent of the size of the non-corporate capital share. But when the non-corporate sector is more labor intensive, the same percentage size reduction in non-corporate employment corresponds to a larger change in the number of workers who switch to the corporate sector. This in turn leads to a greater percentage increase in corporate employment, since the corporate employment base is smaller and thus the inflow of new workers has a greater impact. This reallocation of workers across sectors thus leads to a larger output response to a corporate tax cut with a smaller capital income share, but only if we view the changes in capital share as mainly arising from the non-corporate sector.

A Dynamic Model

We now show that these same forces apply in dynamic model and can generate results which are consistent, at least qualitatively, with our empirical results. As in one of the one-sector models we discussed on above, we consider a small open economy model with incomplete markets. Now for simplicity we take the exogenous interest rate to be constant, and thus look just at the impact of the tax cut on a small open economy like a state. However now, unlike in the one-sector models above, production is split between a corporate and a non-corporate sector that produce different goods. Households consume C_t which is a CES aggregate of the goods produced in each sector:

$$C_t = \left(\phi_C^{\frac{1}{\eta}} C_{Ct}^{\frac{\eta-1}{\eta}} + (1-\phi_C)^{\frac{\eta-1}{\eta}} C_{Nt}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}},$$

where ϕ_C the weight on the corporate good and η gives the elasticity of substitution. As $\eta \to \infty$ and $\phi_C \to 1$ the outcomes from this model converge to those from the one sector model. We focus on the case of $\eta = 2$, which is the same as the value Nakamura and Steinsson (2014) use for the substitution elasticity between domestic and foreign goods, but similar results hold for other elasticities. As in the static model above, the corporate good is numeraire and P_{Nt} is the relative price of the non-corporate good. Then the aggregate price level P_t satisfies:

$$P_t = \left(\phi_C + (1-\phi_C)P_{Nt}^{1-\eta}\right)^{\frac{1}{1-\eta}} .$$

As above, sectors differ in their capital share α_i, and each sector has its own capital stock and hires labor from a common pool of workers. We also add quadratic investment adjustment costs, which change the shape of the impulse response functions but do not affect any of the qualitative results.

Figure 23: Impulse responses of output and employment to a corporate shock in a two sector model with incomplete markets.

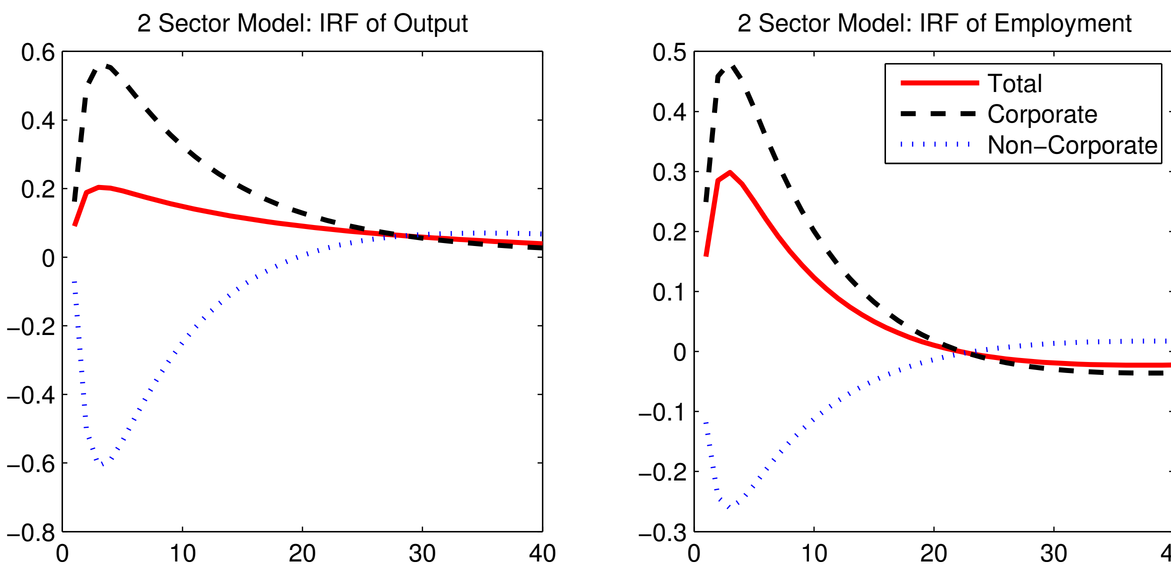


Figure 23 illustrates how in our dynamic model reallocation across sectors occurs in response to a shock. We discussed this reallocation in the static model above, and it is the key difference between our one and two sector models. In particular, Figure 23 shows the responses of output and employment in the corporate and non-corporate sector to the corporate tax cut, along with the response of aggregate output and employment (which is the weighted average across sectors). We see that the sectoral responses are much larger in magnitude than the aggregate, with employment increasing sharply in the corporate sector but falling in the non-corporate sector in response to the cut. On net, this generates a positive hump-shaped response of employment to the shock. Similarly, output jumps on impact in the corporate sector with the reallocation of workers, and continues to increase in a hump-shaped fashion as increased investment leads to a buildup of capital in the sector. In the non-corporate sector, output falls with the reallocation of factors to the corporate sector, and on-net the aggregate impact is a smaller positive but prolonged output response.

We now focus on impulse responses from the model for differing levels of the capital share parameters in the two sectors, α_C and α_N. In each case we calibrate the model so that 67% of output is produced in the corporate sector, which is roughly the long-run average share from the data. In practice this involves changing the consumption share parameter ϕ_C as we change α_C or α_N in order to keep the sector size constant. In the US, the share of business income from corporations has been trending down over time and this value is a rough midpoint. The exact value of the share of output produced by corporations is relatively unimportant for our qualitative results. But it is important that we keep it fixed across specifications, as it ensures that our results are consistent with our empirical finding above that the size of the corporate sector is uncorrelated with capital's share across states.

In Figure 24 and 25 we plot the impulse responses and cumulative responses of output to a corporate tax shock. In Figure 24 we fix capital's share in the non-corporate sector at $\alpha_N = 0.4$ and show the results for two different values of capital's share in the corporate sector α_C. Our results here are similar to those in one sector models, and also are consistent with the static model above. Increasing capital's share in the corporate sector leads to a larger response of output to a corporate tax shock, which runs counter to our empirical results above. Figure 25 considers a similar exercise, but now we fix capital's share in the corporate sector at $\alpha_C = 0.35$ and show the results for two different

Figure 24: Impulse response and cumulative response of output to a corporate tax shock in a two sector model with incomplete markets.

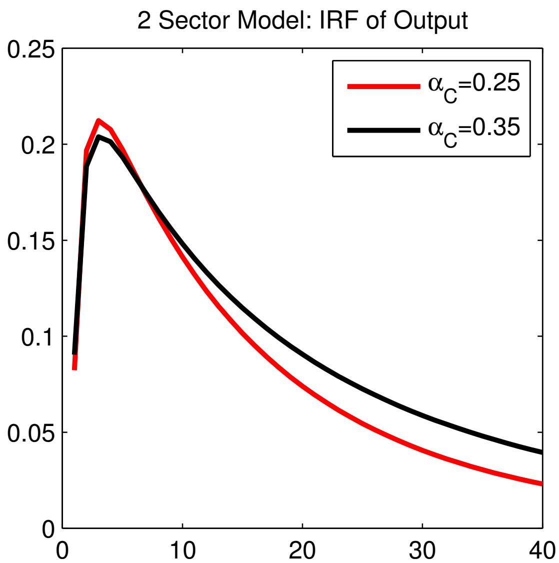
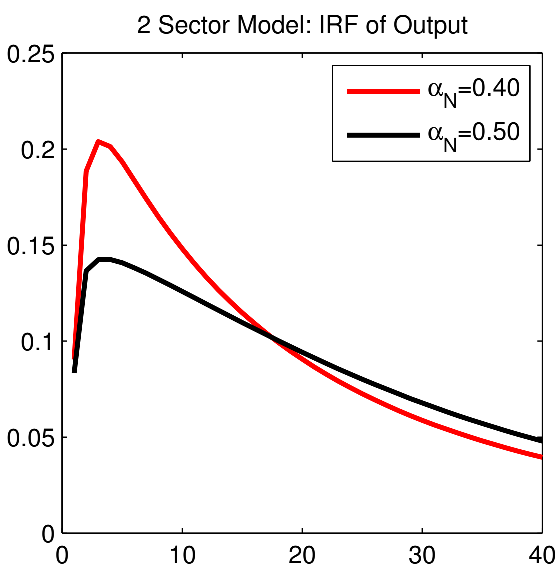


Figure 25: Impulse response and cumulative response of output to a corporate tax shock in a two sector model with incomplete markets.



values of capital's share in the non-corporate sector α_N. Here we see that the response of output to the corporate tax cut, both on impact and cumulatively, is larger with a smaller non-corporate capital's share, which is consistent with our empirical results. The intuition for this result also consistent with the static model described above, as a smaller non-corporate capital share leads to a larger reallocation of workers from the non-corporate to the corporate sector in response to the tax cut.

3.4 Conclusion

In this paper we have documented substantial heterogeneity across states in their responses to federal tax shocks. In addition to the sharp differences in the estimated magnitude of the responses, more than half of all states have no statistically significant response to either tax change. We also find robust evidence that states which have a smaller capital's share of income have larger output and employment responses to reductions in corporate tax rates. While this result is puzzling from the vantage point of a standard one-sector model, it is consistent with a model that includes corporate and non-corporate sectors. Overall, our results point to the importance of regional variation in understanding the impact of policy changes, and suggest that factor reallocation across states and sectors plays an important role in generating the aggregate impacts of federal tax changes.

Our results in this paper suggest new avenues for future research. In particular, our theoretical framework has suggested the importance of sectoral reallocation, but we have not directly tested the empirical importance of this mechanism. Several economic indicators, including the capital data from McMurry and Williams (2018), are available by state and industry, so this is a potentially viable. However one important qualification is that the data is broken out by industry, not by corporate or non-corporate status as the theory suggests is important. Nonetheless, the theory also has predictions for the relative movements in prices and wages across states in response to the corporate tax cut, which we could confront with the data. Moreover, we have more disaggregated data by industry at the state level. It would be worth investigating whether the results we have found for statewide aggregates also across industries within a state and within a given industry across states.

In addition, while our results show the importance of heterogeneity and interactions across states and sectors, the models we have analyzed here have been relatively limited along those dimensions. Further, we have shown that the theory can qualitatively match the empirical findings, but have not considered whether the model can fit the facts quantitatively. In ongoing work we are considering a more complete multi-state equilibrium model which allows for rich interactions and dependencies across states. In addition to addressing differential responses to federal policy, this model will allow us to study a wide array of issues and allow for policy evaluation at the federal and state levels.

Appendix A

Regional Risk and Aggregate Fluctuations

A.1 Data Sources

A.1.1 State-Level Data

Output. State GDP data is available at BEA Regional Economic Accounts. Annual real GDP data range from 1987 up to now and nominal GDP data span from 1963 up to now. To construct a relatively long sample of real GDP by state, I make the following changes to the raw output data to take into account several discontinuities. First, I keep the annual real GDP data for the post-1997 period, it is denominated in chained 2009 dollars and based on the 2007 North American Industry Classification System or NAICS. Second, I transform the annual real GDP data from 1987 to 1997 (chained 1997 dollars, and based on the 1987 Standard Industrial Classification or SIC) such that the GDP data for 1997 is the same between the two annual datasets before and after 1997. Lastly, I apply a national GDP deflator [1] to state nominal GDP for the years 1963-1987 (based on 1972 SIC), and adjust uniformly the "real GDP" between 1963-1987 such that 1987 real output is the same with the that of the previous step to control for the impact of change in statistical methods. The output following the above procedures is an approximate state-level real GDP (in chained 2009 one million dollars) dataset at annual frequency during 1963-2004 and quarterly during 2005-2017.

Consumer Price Index. For state-level CPI, I follow the approximation approach in Herkenhoff et al. (2018) and extend their series to 2017.

[1] Implicit state price deflator is unavailable until 2008.

Personal Income. Nominal personal income and disposable personal income data are available from BEA Regional Accounts since 1948. They are transformed to real values using regional CPI data, with 2009 as the base year.

Consumption. Official state-level consumption expenditure data are collected from the BEA Regional Economics Accounts. However, data is only available annually between 1997 and 2016 in nominal terms. For data before 1997, I follow some regional risk sharing literature (Asdrubali et al., 1996; Del Negro, 2002; Devereux and Hnatkovska, 2019) where total private consumption is calculated as the retail sales in each state times the ratio of total retail sales to total consumption in the United States. The data on total personal consumption expenditures is obtained from NIPA tables; and data on state-level retail sales come from the Sales & Marketing Management's Annual Survey of Buying Power. This annual survey dataset samples from 1960 to 2005 (1999 missing); the 1960-1995 data are kindly provided by Marco Del Negro which he use in Del Negro (2002), and the 1996-2005 data are recorded directly from this magazine using the Optical Character Recognition technology. I then apply the state price index to this nominal consumption series and obtain an annual-frequency real consumption (in 2009 million dollars) dataset for each state.

Federal Fiscal Transfer and Taxes. Under the "Annual State Personal Income and Employment" section of the BEA Regional Accounts are the data on personal current transfer receipts, most of which come from the subcategory "current transfer receipts of individuals from governments". Current transfer receipts of individuals from governments consist of: retirement and disability insurance benefits, medical benefits, income maintenance benefits, unemployment insurance compensation, veterans' benefits, education and training assistance, and other transfer receipts of individuals from governments. Federal taxes represent the sum of the income taxes that are withheld, usually by employers, from wages and salaries; the quarterly payments of estimated taxes on income that is usually not subject to withholding; and final settlements, which is additional tax payments that are made when the tax returns for a year are filed or as a result of audits by the Federal Government. And income tax returns are netted out of these gross taxes when calculating personal current federal taxes.

A.1.2 Aggregate Data

The key aggregate variables used in this study are GDP, personal income and personal consumption expenditures, all in real per capita terms. These data are standard and can be conveniently accessed through the FRED database.

A.2 Supplementary Results

A.2.1 Cross-Sectional Dispersion in a Long Time Series

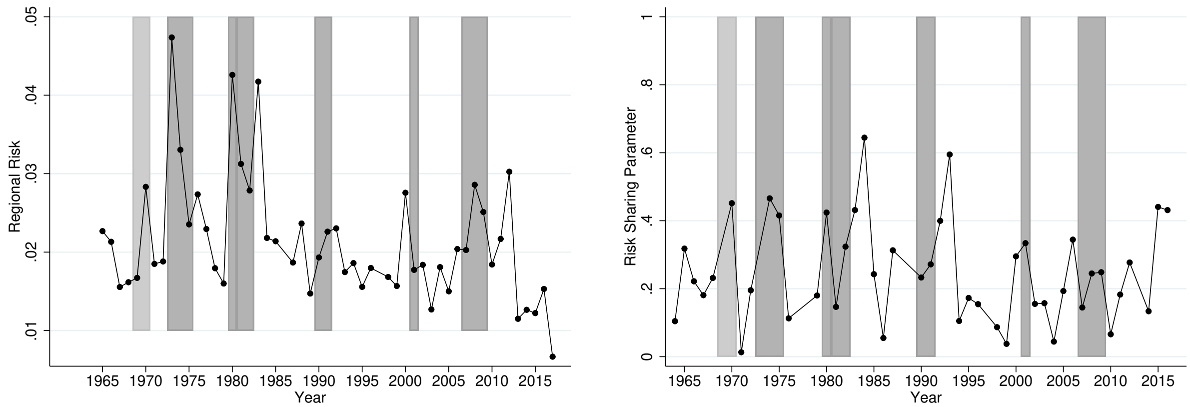
Figure 26: Cross-Sectional Dispersions in the Whole Sample

Notes: Left: cross-sectional conditional standard deviation of personal income growth, disposable income growth, and GDP growth across regions for each year. Right: cross-sectional conditional standard deviation of consumption growth. All series are in real per capita terms.

A.2.2 GMM Estimates for φ_t^χ and $\sigma_{\chi,t}$

Figure 27 plots the yearly GMM estimation results for φ_t^χ and $\sigma_{\chi,t}$.

Figure 27: Plot of GMM Estimates



Notes: Estimates for year 1997 are omitted from both series as it's the connecting of two consumption series. For the risk sharing parameter estimates, I plot only the ones in the range of $(0, 1)$. There's one estimate of φ^{χ} greater than 1, and only a couple less than 0. Shaded areas are NBER recessions. These estimates come from an exactly identified system using growth rates.

A.2.3 Error-Correction OLS Results

One may be worried that regional and aggregate variables, especially consumption, may have a long-run equilibrium relationship, from which the last-period's deviation may influence the actual short-run dynamics. With the concern that regional and aggregate consumption may be cointegrated, I add an error-correction term to estimation equation (1.7). In particular, I assume that $\log c_{i,t}$ and $\log c_t$ are both not stationary but $\log c_{i,t} - \log c_t$ is, that is, there's long-run complete risk sharing. Table 12 reports the OLS estimation results accounting for an error-correction term. The first row reports the β_1^{ec} estimates, all of which are slightly below 0 and strongly significant. This confirms our conjecture of a mean-reverting process for regional consumption in levels relative to the aggregate. However, adding this term to the standard test of consumption risk sharing equation doesn't alter the estimates of the core risk sharing coefficient β_1, or the comparison of risk sharing between normal and recession times.

$$\begin{aligned}\Delta \log c_{i,t} - \Delta \log c_t =& \beta_0 + \beta_1^{ec}(\log c_{i,t-1} - \log c_{t-1}) + \beta_1(\Delta \log y_{i,t} - \Delta \log y_t) \\ &+ \beta_1^{rec}\left[(\Delta \log y_{i,t} - \Delta \log y_t) \times \mathbb{I}(recession)\right] + \nu_i + u_{i,t}\mathbb{I}(t \leq 1997) + \epsilon_{i,t}\end{aligned} \tag{A.1}$$

Table 12: Regional Risk Sharing: Error-Correction OLS Estimation Results

	$y = GDP$			$y = PersonalIncome$		
	A	B	C	A	B	C
Err-Corr Term	-0.096***	-0.039***	-0.095***	-0.089***	-0.037***	-0.089***
	(0.010)	(0.005)	(0.010)	(0.009)	(0.005)	(0.009)
$\Delta \log GDP$	0.187***	0.192***	0.199***			
	(0.041)	(0.039)	(0.050)			
$\Delta \log GDP \times Rec$			-0.033			
			(0.085)			
$\Delta \log PI$				0.247***	0.253***	0.274***
				(0.069)	(0.069)	(0.068)
$\Delta \log PI \times Rec$						-0.076
						(0.061)
Constant	-0.657***	-0.269***	-0.657***	-0.613***	-0.254***	-0.611***
	(0.067)	(0.037)	(0.067)	(0.060)	(0.034)	(0.059)
N	2544	2544	2544	2688	2688	2688

Notes: Clustered robust standard errors are reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sample size is 48 states, leaving Alaska, DC, and Hawaii out. Columns 2-4 show the results of risk sharing OLS regressions using regional GDP as the independent variable. Columns 5-7 show the results using regional personal income as the independent variable.

A.2.4 Decompose "Net" Transfers

Table 13 provides additional evidence on what drives the "state-contingency" of the U.S. tax-and-fiscal transfer system by decomposing the net transfer with total transfer and total tax, and replicating the results in Table 5 using these two components respectively.

Table 13: Fiscal Transfer & Tax before and during the Great Recession

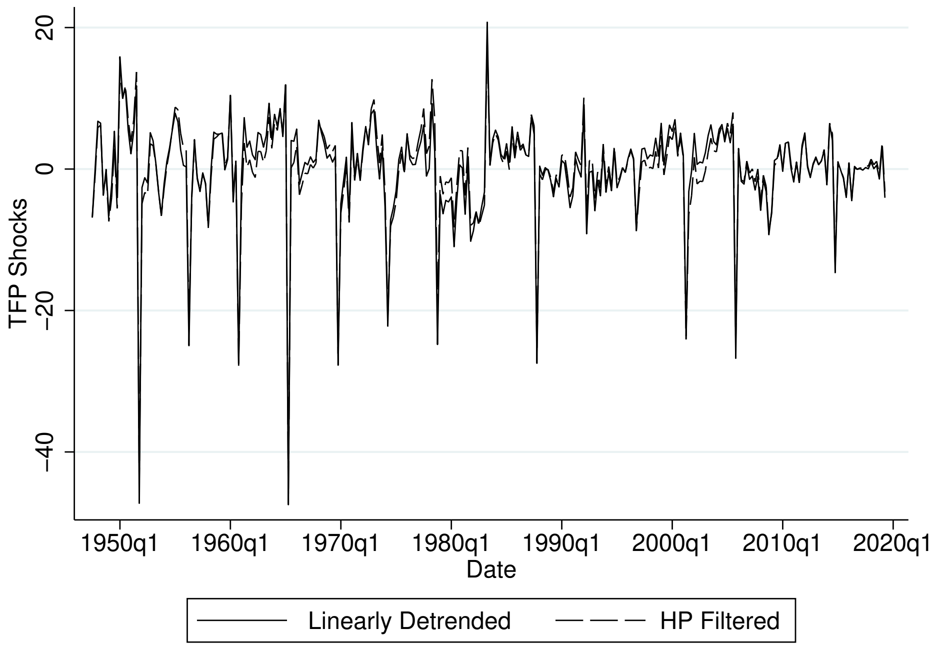
	Total Transfers				Total Tax			
	OLS		IV		OLS		IV	
	(06-10)	(02-06)	(06-10)	(02-06)	(06-10)	(02-06)	(06-10)	(02-06)
GDP Growth (06-10)	-0.329***		-0.622***		1.192***		1.292***	
	(0.082)		(0.145)		(0.187)		(0.191)	
GDP Growth (02-06)		-0.129		-0.102		1.001***		2.593***
		(0.169)		(0.394)		(0.337)		(0.933)
Constant	6.009***	2.068***	5.839***	2.012***	-4.242***	-0.162	-4.184***	-3.472*
	(0.145)	(0.343)	(0.171)	(0.767)	(0.282)	(0.677)	(0.233)	(1.919)
N	48	48	48	48	48	48	48	48

Notes: Robust standard errors are reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sample size is 48 states, leaving Alaska, DC, and Hawaii out.

A.2.5 Estimated TFP Shocks

This figure supplements the short-sample in Figure 9.

Figure 28: TFP Shocks



Notes: TFP series are retrieved from John Fernald's website. To obtain TFP innovations plotted here, I first detrend the TFP either using a linearly detrending method (solid line) or using HP filters (dashed line). I then fit an AR(1) process to the detrended data. The noises to the AR(1) process are the TFP shocks.

A.3 Derivation of Moment Conditions

The main cross-sectional and cross-time moments used in the exact identification system are:

$$\mathbb{E}_i(\Delta \log y_{i,t}) = \mu_i^y$$

$$\mathbb{E}_i(\Delta \log c_{i,t}) = \mu_i^c$$

$$Var_t(\Delta \log y_{i,t}) = Var(\mu_i^y) + Var_t(\chi_{i,t})$$

$$Cov_t(\Delta \log y_{i,t}, \Delta \log y_{i,t+1}) = Var(\mu_i^y) + Cov(\chi_{i,t}, \chi_{i,t+1})$$

$$= Var(\mu_i^y) + \rho^{\chi} Var_t(\chi_{i,t})$$

$$Cov_t(\Delta \log y_{i,t}, \Delta \log c_{i,t}) = Cov(\mu_i^y, \mu_i^c) + \varphi_t^{\chi} Var(\chi_{i,t})$$

$$Var_t(\Delta \log c_{i,t}) = Var(\mu_i^c) + (\varphi_t^{\chi})^2 Var_t(\chi_{i,t}) + \sigma_c^2 + \sigma_u^2 \mathbb{I}(t \leq 1997)$$

$$Var_t(\chi_{i,t}) = (\rho^{\chi})^2 Var_t(\chi_{i,t-1}) + \sigma_{\chi,t}^2$$

$$\mathbb{E}_t(\Delta \log y_{i,t}) = \mathbb{E}(\mu_i^y) + \Xi_t$$

$$\mathbb{E}_t(\Delta \log c_{i,t}) = \mathbb{E}(\mu_i^c) + \varphi_t^{\Xi} \Xi_t$$

It follows that:

$$\varphi_t^{\chi} = \frac{Cov_t(\Delta \log y_{i,t}, \Delta \log c_{i,t}) - Cov(\mu_i^y, \mu_i^c)}{Var_t(\Delta \log y_{i,t}) - Var(\mu_i^y)}$$

$$\sigma_{\chi,t}^2 = Var_t(\Delta \log y_{i,t}) - Var(\mu_i^y) - (\rho^{\chi})^2 \left(Var_{t-1}(\Delta \log y_{i,t-1}) - Var(\mu_i^y)\right)$$

$$\rho^{\chi} = \frac{Cov_t(\Delta \log y_{i,t}, \Delta \log y_{i,t+1}) - Var(\mu_i^y)}{Var_t(\Delta \log y_{i,t}) - Var(\mu_i^y)}$$

$$\varphi_t^{\Xi} = \frac{\mathbb{E}_t(\Delta \log c_{i,t}) - \mathbb{E}(\mu_i^c)}{\mathbb{E}_t(\Delta \log y_{i,t}) - \mathbb{E}(\mu_i^y)}$$

ρ^{Ξ} and σ_{Ξ} are then estimated by imposing the zero correlation assumption of Ξ_{t-1} and ε_t. Adding overidentification restrictions is easy. I simply generalize the moments above on autocovariance of income process, and covariance of consumption and income to lag s.

$$\begin{aligned} Cov_t(\Delta \log y_{i,t}, \Delta \log y_{i,t+s}) &= Var(\mu_i^y) + Cov(\chi_{i,t}, \chi_{i,t+s}) \\ &= Var(\mu_i^y) + (\rho^\chi)^s Var_t(\chi_{i,t}) \\ Cov_t(\Delta \log y_{i,t+s}, \Delta \log c_{i,t}) &= Cov(\mu_i^y, \mu_i^c) + \varphi_t^\chi Cov(\chi_{i,t+s}, \chi_{i,t}) \end{aligned}$$

In the overidentification results reported in the main text, I add

$$Cov_t(\Delta \log y_{i,t}, \Delta \log y_{i,t+2}),$$

$$Cov_t(\Delta \log y_{i,t+1}, \Delta \log c_{i,t}),$$

$$Cov_t(\Delta \log y_{i,t+2}, \Delta \log c_{i,t})$$

to the exactly identified system.

A.4 Recursive Representation and Solution Algorithm

A.4.1 Firm's Recursive Problem

Equations (1.12) and (1.13) determine the evolution of regional optimal prices and producer prices. I rewrite these equations in a recursive manner as follows

$$\begin{aligned} p_t^{i*} &= \frac{\theta}{\theta - 1} \frac{p_t^i(A)}{p_t^i(B)} \\ p_t^i(A) &= C_{i,t}^{-\gamma} (p_t^i)^{\theta-1} y_t^i MC_{i,t} + \beta\xi \mathbb{E}_t p_{t+1}^i(A) \\ p_t^i(B) &= C_{i,t}^{-\gamma} (p_t^i)^{\theta-1} y_t^i + \beta\xi \mathbb{E}_t p_{t+1}^i(B) \\ p_t^i &= \left[(1-\xi)\left(p_t^{i*}\right)^{1-\theta} + \xi \left(p_{t-1}^i\right)^{1-\theta}\right]^{\frac{1}{1-\theta}} \end{aligned}$$

In addition, as is standard in the New Keynesian literature, I define the efficiency loss due to price dispersion $\Delta_{i,t}$ as follows

$$\Delta_{i,t} = \int_0^1 \left(\frac{p_t^i(k)}{p_t^i}\right)^{-\theta} dk$$

It follows that

$$\Delta_{i,t} = \xi \Delta_{i,t-1} \left(\frac{p_t^i}{p_{t-1}^i}\right)^{\theta} + (1-\xi)\left(\frac{p_t^{i*}}{p_t^i}\right)^{-\theta}$$

Regional labor market clearing implies that

$$A_{i,t} N_{i,t} = y_t^i \Delta_{i,t}$$

A.4.2 Household's Recursive Problem

The problem of the household in region i with nominal asset B_i (corresponding to $B_{i,t-1}$), and regional productivity z_i (corresponding to $z_{i,t}$) can be written as

$$V(z_i, B_i, a, \sigma_z, \mu) = \max_{C_i, N_i, B_i'} \left\{ \frac{C_i^{1-\gamma}}{1-\gamma} - \psi \frac{N_i^{1+\nu}}{1+\nu} + \beta \mathbb{E} V(z_i', B_i', a', \sigma_z', \mu') \right\}$$

subject to

$$PC_i + B_i' = R(\mathcal{S}_{-1}) B_i + W_i N_i + T_i + \Pi_i$$

$$B_i' \geq -b$$

Subscript i is omitted for regional consumption price since it's equalized across the nation. F.O.C. of the household's problem:

$$C_i(s_i, \mathcal{S})^{-\gamma} \geq \beta R(\mathcal{S}) \mathbb{E}\left[C_i(s_i', \mathcal{S}')^{-\gamma}\right]$$

with equality if $B_i' > -b$. $C_i(s_i, \mathcal{S}) = (R(\mathcal{S}_{-1})B_i + p_t^i y_t^i + T_i - B_i')/P$ is the optimal consumption.

Intratemporal optimization implies the supply of labor hours

$$N_i(s_i, \mathcal{S}) = \left(\frac{C_i(s_i, \mathcal{S})^{-\gamma} W_i}{\psi P}\right)^{1/\nu}$$

A.4.3 Numerical Solution: 3 Steps

Step 1: approximate equilibrium using parametric functions of density of state variables. There are two objects to approximate in this step. First, I approximate the cross-sectional distribution of individual state variables (z_i, B_i) using the same parametric function as in Winberry (2018). In particular, I set the degree of polynomials to 3 in the baseline computation, to allow for non-normal features, such as skewness or excess kurtosis. From this approximation, we could derive the exact mapping from functional parameters to a vector of moments, which completely characterize the infinite-dimensional distribution. Then the law of motion of the distribution could be replaced by a finite number of equations describing the law of motion for these moments. Second, I approximate the value function V with respect to individual states using orthogonal Chebyshev polynomials. Decision rules are computed from the parametric value function via first order conditions. With all these approximations above, the recursive equilibrium replaces the distribution component in the true aggregate state with the vector of moments; replaces the Bellman equation with the Chebyshev approximation, and the true law of motion with the law of motion of moments, leaving us with a familiar form of residual function studied in Schmitt-Grohe and Uribe (2004).

Step 2: compute a stationary equilibrium of the approximated equilibrium functions in the previous step, assuming no aggregate shocks. I solve the system in terms of a single non-linear equation in the aggregate bond holdings B.

Step 3: compute and simulate aggregate dynamics using perturbation methods. At this stage, we have solved the stationary equilibrium objects in the previous step, together with a system of nonlinear equations that the model has to satisfy. We proceed to compute the aggregate dynamics subject to aggregate shocks as a linear rational expectations model using standard perturbation methods in Dynare.

Appendix B

State-Level Implications of Federal Tax Policies

B.1 Data

B.1.1 Data Construction for the Mixed-Frequency Estimation

Output. State GDP data is available at BEA Regional Economic Accounts. Quarterly real GDP by state is not available until 2005Q1; annual real GDP data ranges from 1987 up to now; nominal GDP data spans from 1963 up to now. To construct a relatively long sample of real GDP by state, we make the following changes to the raw output data:

- Keep the recent quarterly real GDP data (2005Q1-) and annual real GDP data (1997-2004), both of which are in chained 2009 dollars and based on the 2007 North American Industry Classification System or NAICS.

- Transform the annual real GDP data from 1987 to 1997 (chained 1997 dollars, and based on the 1987 Standard Industrial Classification or SIC) such that the GDP data for 1997 is the same between the two annual datasets before and after 1997.

- Apply a national GDP deflator [1] to state nominal GDP for the years 1963-1987 (based on 1972 SIC), and adjust uniformly the "real GDP" between 1963-1987 such that 1987 real output is the same with the that of the previous step to control for the impact of change in statistical methods.

[1] Implicit state price deflator is unavailable until 2008.

The output following the above procedures is an approximate state-level real GDP (in chained 2009 one million dollars) dataset at annual frequency during 1963-2004 and quarterly during 2005-2017.

Personal Income. We obtain personal income data from BEA Regional Accounts. Nominal personal income data at quarterly frequency is available since 1948Q1 (Alaska and Hawaii since 1950Q1). This data is already seasonally adjusted at annual rates.

Total Expenditure. We compile state total expenditure data from the Census Annual Survey of State & Local Government Finances. Historical data between 1993 and 2016 is available here, where we pick the state (excluding local) total expenditure. Data from 2012-2016 are available on the American Fact Finder too. Data in 1993-2011 are collected by reading the "State & Local Government" files. Historical data prior to 1993 is stored here.[2] This dataset spans fiscal years from 1951 to 2008. And we pick 1963-1992 and combine it with the 1993-2016 data described above.

Capital Investment. Real capital data by state, 1963-2016, from the calculation of McMurry and Williams (2018). In particular, McMurry and Williams (2018) estimate the state-level capital within an industry by allocating nationwide capital in that industry across states. In particular, they assume that capital is perfectly mobile within but not across sectors and that output market is perfect competitive. Let i denote the state, j the industry and t the time. Since $R_{ijt} = R_{jt}$, it follows that $K_{ijt} = \frac{R_{ijt}K_{ijt}}{R_{jt}K_{jt}}K_{jt}$. Since $R_{ijt}K_{ijt}$ and $R_{jt}K_{jt}$, as measures of capital income, are both observable in the BEA gross operating surplus (GOS) by state and industry, as well as K_{jt} as the nationwide capital by industry, they could estimate a capital series by state and industry (K_{ijt}), summing up to a state capital series (K_{it}).

Price Index. For state CPI, we follow the approximation approach in Herkenhoff et al. (2018) and extend their series to 2017.

PCE. We collect state consumption expenditure from the BEA Regional Data. However, data is only available annually between 1997 and 2016 in millions of *current* dollars.

[2] We thank a Census EWD staff for sharing this file which was not public on the website.

We apply the state price index to this nominal consumption series and get a annual-frequency real consumption (in 2009 million dollars) dataset for each state.

Employment. Total Non-farm Employment[3] is from BLS-CES State and Metro Area Databases (link). Monthly data is available and we compute the quarterly average, in order to be consistent with the data frequency of most other variables. Raw data before 1990 is not seasonally adjusted and we apply the X-13 program of U.S. Census Bureau to the sample in this period.

Unemployment Rate. Unemployment Rate data is from the BLS Local Area Unemployment Statistics, seasonally adjusted at monthly frequency. Similarly, we compute its quarterly average. This data is available after 1976.

State Tax Collection. There are two sources that our tax collection data is based on. Quarterly tax collection 1994Q1-2017Q4 comes from Quarterly Summary of State & Local Tax Revenue (TAX link)[4]. To make up for the missing quarterly tax data before 1994, we collect annual data for 1963-1993 from Annual Survey of State Government Tax Collections (STD link). We apply the X-13 program to the quarterly series, and adjust them in annual rate.

National Block. We obtain the S&P 500 Index from "CRISP Index File on the S&P 500". All the rest are from FRED. GDP, consumption, government expenditure, investment, and personal income data are real (in chained 2009 Dollars). All the macro series are seasonally adjusted. We convert, if needed, the high-frequency series to the quarterly frequency.

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[3]Total employment including the farm sector is desirable for our exercise but unfortunately unavailable.

[4]This dataset provides quarterly estimates of state and local government tax revenue at a national level, as well as detailed tax revenue data for individual states. This quarterly survey has been conducted continuously since 1962. The information contained in this survey is the most current available on a nationwide basis for government tax collections.

Table 14: List of National Variables from FRED

Variable Name	FRED Name
Gross Domestic Product	GDPC1
Government Expenditures	GCEC1
Personal Consumption Expenditures	PCECC96
Consumer Price Index	CPIAUCSL
Gross Private Domestic Investment	GPDIC1
Unemployment Rate	UNRATE
Personal Income	RPI
Total Nonfarm Payroll Employment	PAYEMS
10-year Treasury Bond Yield	GS10
Federal Funds Rate	FEDFUNDS
Moody's Seasoned BAA Corporate Bond Yield	BAA

B.1.2 Extending the Legislated Tax Shocks Data in Mertens and Ravn (2013)

We extend the individual and corporate income tax shock data documented in Mertens and Ravn (2013) that spans 1950-2006, following the "policy motivation" guidelines of Romer and Romer (2010). *Endogenous* tax actions are "ones taken to offset developments that would cause output growth to differ from normal". These actions include the countercyclical changes made when policymakers are forecasting a recession or responding to current or projected economic conditions; and spending-driven changes made to counteract the government spending, e.g. the increase in payroll taxes that accompanied the introduction of Medicare program in 1965. *Exogenous* tax changes are those "not taken to offset factors pushing growth away from normal", including: changes motivated by a belief that lower marginal tax rates will raise output in the long run; changes of tax to deal with an inherited budget deficit, that "reflects past economic conditions and budgetary decisions, not current conditions or spending changes." "If policymakers raise taxes to reduce such a deficit, this is not a change motivated by a desire to return growth to normal or to prevent abnormal growth. So it is exogenous." [5]

We also follow Mertens and Ravn (2013) that discard tax changes where implementation lag is more than 1 quarter so that all the shocks involved are unanticipated; and provide subcomponents of the legislated tax actions, i.e. individual income (II) tax shocks (including employment income tax changes) and corporate income (CI) tax shocks. From 2007 to 2017, major tax reforms are as follows:

- 2007-2008, crisis time: **Economic Stimulus Act**, and the **Emergency Economic Stabilization Act of 2008**. They are clearly endogenous policy shocks.

- 2009: **American Recovery and Reinvestment Tax Act of 2009**. Economic Report of the President (2017) says: "As the name of the Act suggests, the intention was for the bill to both generate recovery from the crisis and to be an important investment in the future of the economy." "Importantly, while the Recovery Act provided a considerable short-term boost to aggregate demand, its investments were targeted for their long-term growth potential, helping ensure that the United States climbed out of the crisis stronger than before." Since the main focus of this act is to help bring economy back to normal instead of improve the long-run growth. These are endogenous tax shocks.

- 2010: **Affordable Care Act** that passed in March 2010. The primary goal for this act is to "make affordable health insurance available to more people". Hence the majority of the tax changes in this act is related to health insurance specifically. However, there were several changes on investment income (the surtax on investment income) and payroll tax (hike in Medicare payroll tax). Since they did not take effect until 2013, we do not include them in our extended sample of narrative tax changes either.

- 2011: **The Tax Relief, Unemployment Insurance Reauthorization and**

[5] Romer and Romer (2010).

Job Creation Act of 2010. Economic Report of the President (2011) says: "Government policy has supported the recovery during 2009 and 2010, and the Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act, the compromise tax framework signed into law by the President on December 17, 2010, will help the economy in 2011." These are long-run exogenous tax shocks. Most of the tax changes in this act are simply extensions of previous tax policies. According to Romer and Romer (2010), these changes are not recorded into our sample. One exception is on "Title VI: Temporary Employee Payroll Tax Cut". We obtain the CBO estimates for Title VI, which is accrued to employment tax liability change (classified under individual income tax change in Mertens and Ravn (2013)), with an amount of -67.239 billions.

So II tax change in 2011Q1 was -67.239 billions.

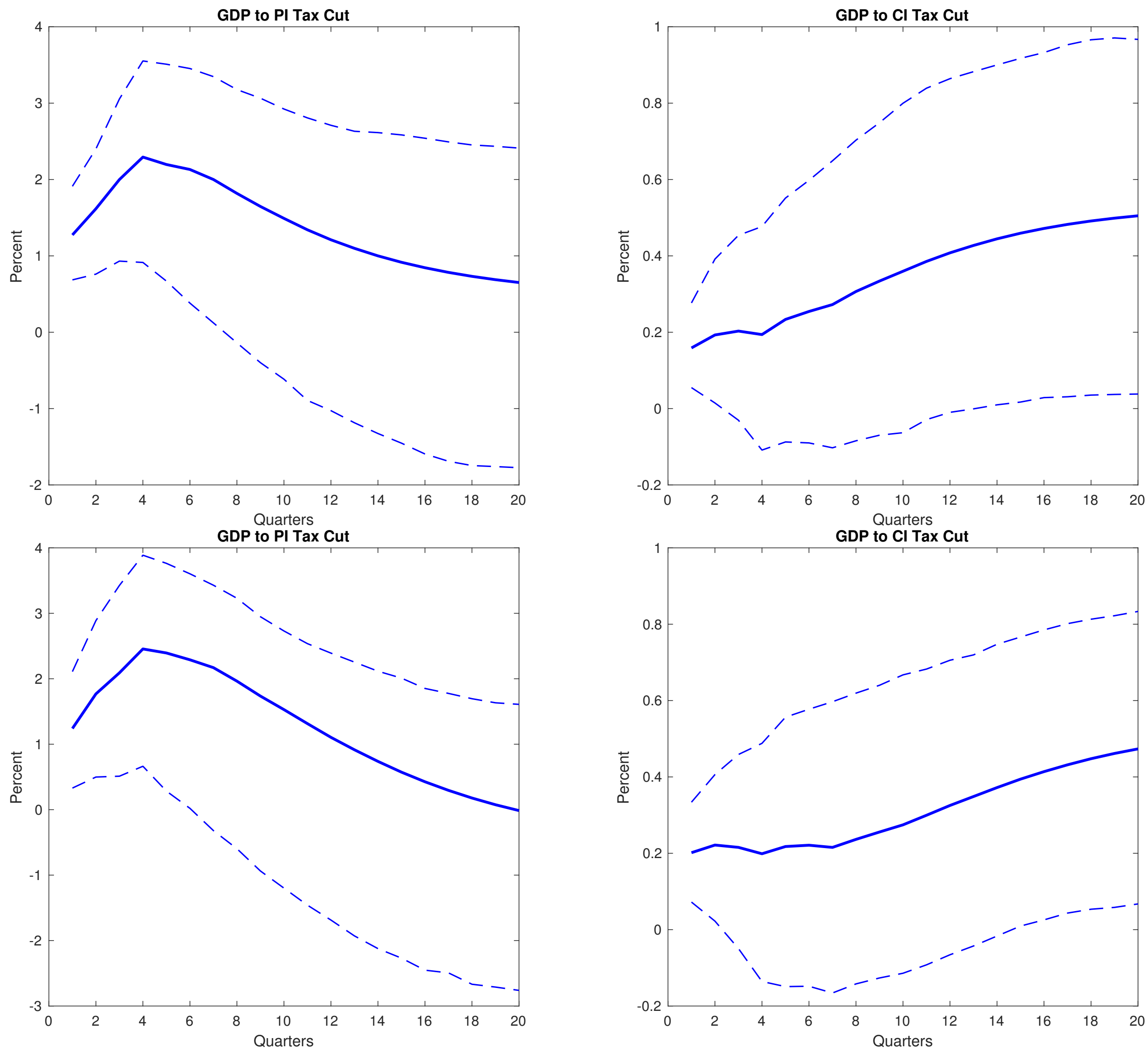
- 2013: **The American Taxpayer Relief Act of 2012** that passed on 1/1/2013. The Act centers on a partial resolution to the US fiscal cliff. So they belong to the deficit-driven exogenous tax shocks.

  II tax change in 2013Q1 was -5.901 billions; CI tax change at the same period was -63.033 billions.

- 2018: **Tax Cuts and Jobs Act, Passed Dec 2017.** Exogenous for sure, but not in our estimation time frame.

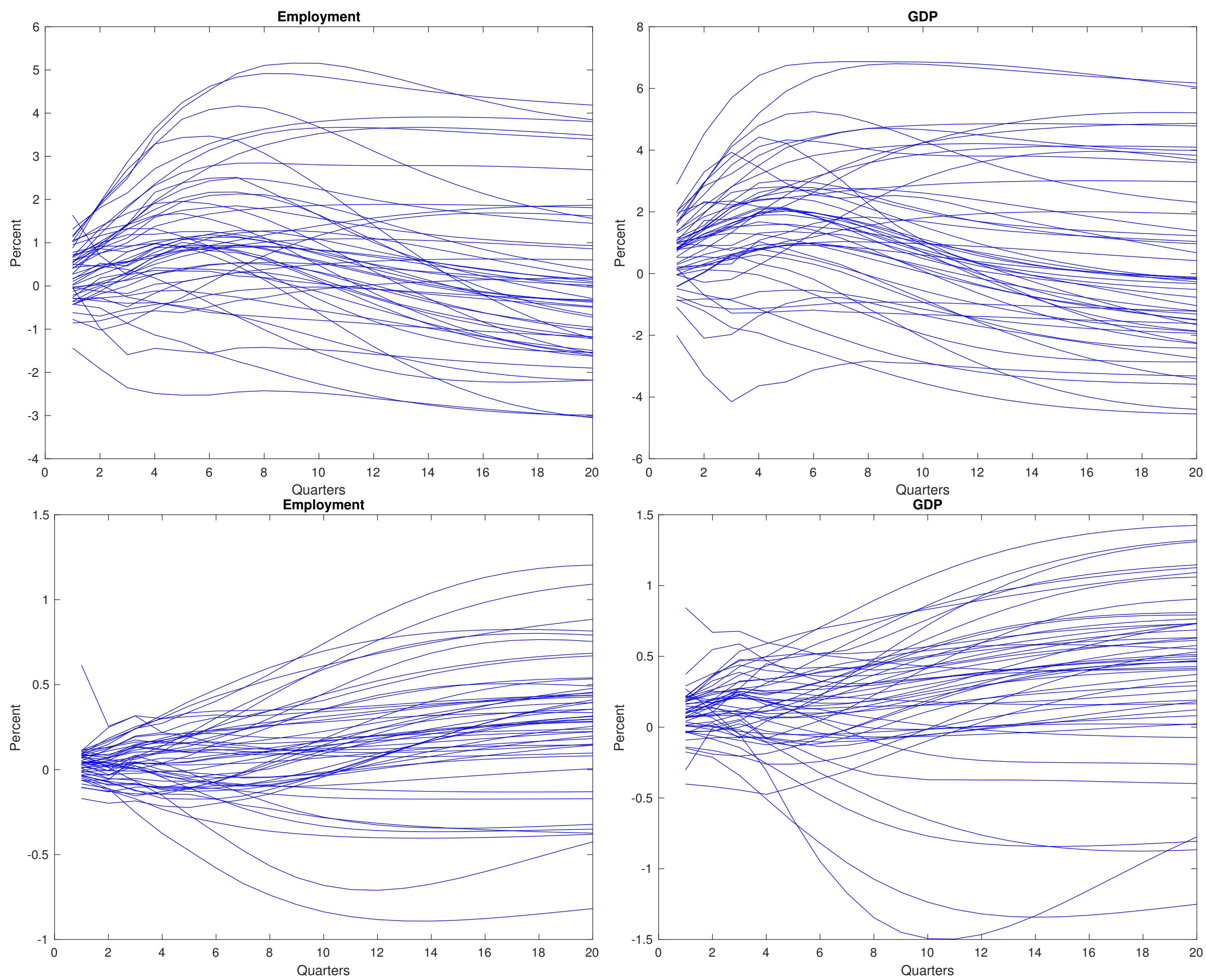
B.2 Additional Empirical Results

Figure 29: Aggregate Impulse Responses



Notes: This figure shows the impulse responses of GDP to personal or corporate income tax cuts. The top two correspond to a SVAR with three aggregate variables: APITR, ACITR and log real GDP; and the bottom two correspond to a SVAR with five aggregate variables: APITR, ACITR, log real GDP, log real Government Expenditures, and log real Federal Government Debt. All of the macro variables are from the Mertens and Ravn (2013) data source, but not divided by total population, and with a longer sample period: 1964Q1 – 2017Q4.

Figure 30: Impulse Responses: Benchmark



Notes: The top two figures show the impulse responses of employment and GDP to a -1% shock to the average federal personal income tax rate, where APITR is ordered second in the SVAR; the bottom two figures show the impulse responses of employment and GDP to a -1% shock to the average federal corporate income tax rate, where ACITR is ordered second in the SVAR.

Table 15: Average State Tax Rates and Capital Share of Income

State Name	Individual Income Tax	Corporate Income Tax	Sales Tax	Capital Share
AL	2.18	5.48	4.00	0.35
AK	0.21	9.40	0.00	0.40
AZ	2.10	8.84	4.62	0.36
AR	2.78	6.32	4.27	0.39
CA	2.60	9.17	5.52	0.35
CO	2.31	4.97	2.99	0.35
CT	1.81	9.82	6.17	0.33
DE	3.05	8.70	0.00	0.41
FL	0.00	5.42	5.02	0.33
GA	2.81	6.00	3.51	0.35
HI	3.89	6.22	4.00	0.33
ID	3.32	7.75	4.42	0.40
IL	2.06	7.07	5.23	0.34
IN	2.18	7.73	4.64	0.35
IA	3.04	11.81	4.13	0.42
KS	2.46	7.07	4.17	0.37
KY	2.96	7.33	7.13	0.37
LA	1.70	8.00	3.43	0.45
ME	3.23	8.74	5.10	0.31
MD	2.64	7.00	4.79	0.32
MA	3.56	9.40	4.49	0.32
MI	2.70	2.51	4.79	0.31
MN	3.69	10.27	5.20	0.35
MS	1.97	4.90	5.89	0.37
MO	2.27	5.83	3.78	0.34
MT	2.70	6.68	0.00	0.39
NE	2.61	7.26	3.84	0.40
NV	0.00	0.00	5.10	0.33
NH	0.25	7.95	0.00	0.33
NJ	2.04	9.00	5.32	0.32
NM	2.11	7.67	4.38	0.41
NY	3.51	8.50	3.75	0.33
NC	3.58	6.92	3.68	0.35
ND	1.28	9.45	4.36	0.42
OH	2.37	8.00	4.74	0.33
OK	2.61	5.94	3.38	0.38
OR	4.44	6.85	0.00	0.37
PA	2.02	9.75	5.89	0.32
RI	2.50	8.97	6.13	0.31
SC	2.90	5.29	4.64	0.32
SD	0.00	0.00	3.92	0.45
TN	0.34	6.08	5.23	0.35
TX	0.00	0.00	4.95	0.39
UT	3.09	4.89	4.52	0.35
VT	2.58	8.74	4.00	0.32
VA	2.78	6.00	3.40	0.31
WA	0.00	0.00	5.76	0.35
WV	3.03	11.27	4.83	0.34
WI	3.58	7.90	4.47	0.33
WY	0.00	0.00	3.40	0.46

Figure 31: Impulse Responses to -1% Federal Personal Income Tax Rate Shock (Personal Income and Employment in SVAR)

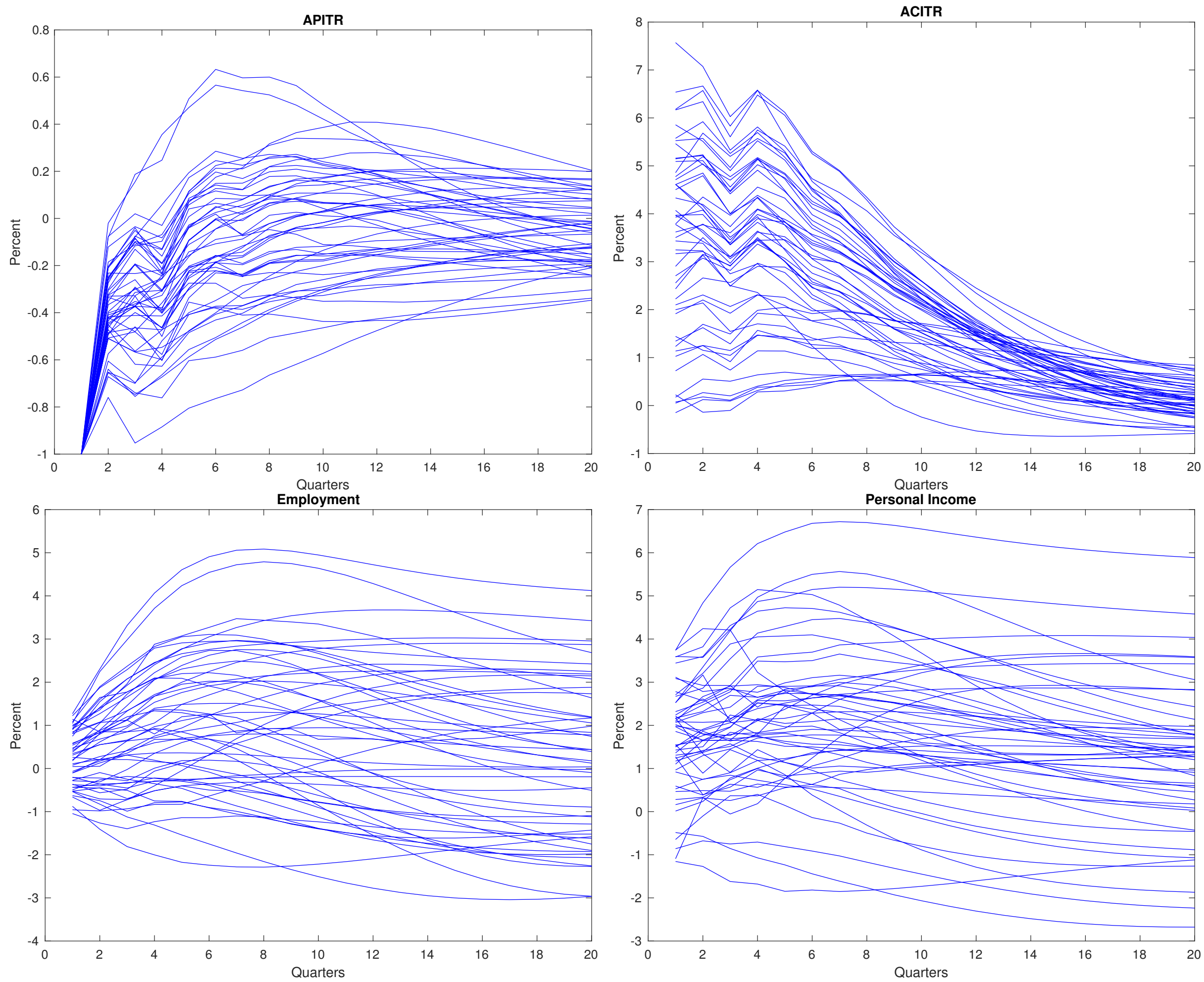


Figure 32: Impulse Responses to -1% Federal Corporate Income Tax Rate Shock (Personal Income and Employment in SVAR)

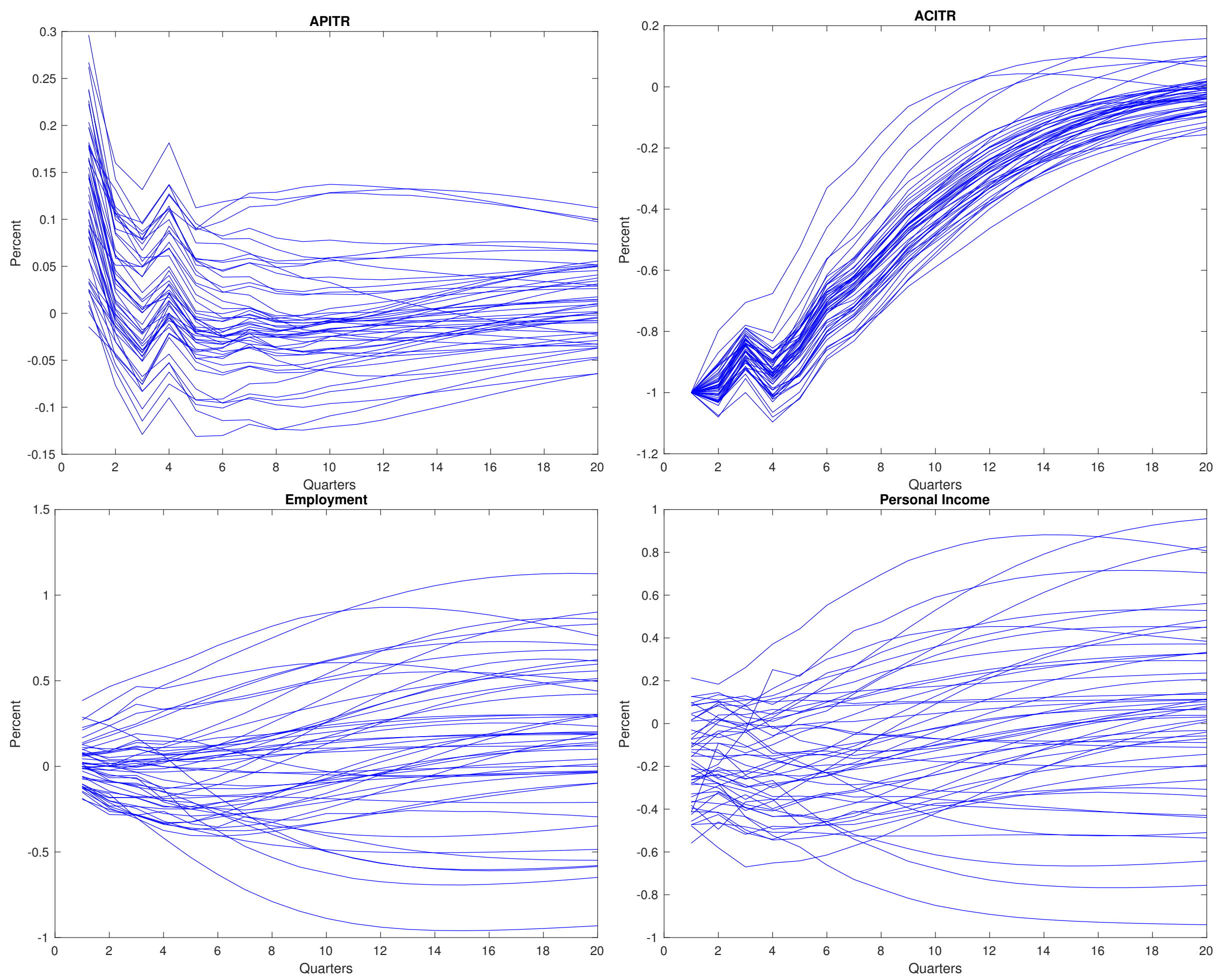


Figure 33: Cumulative Response by State (with State Government Expenditure)

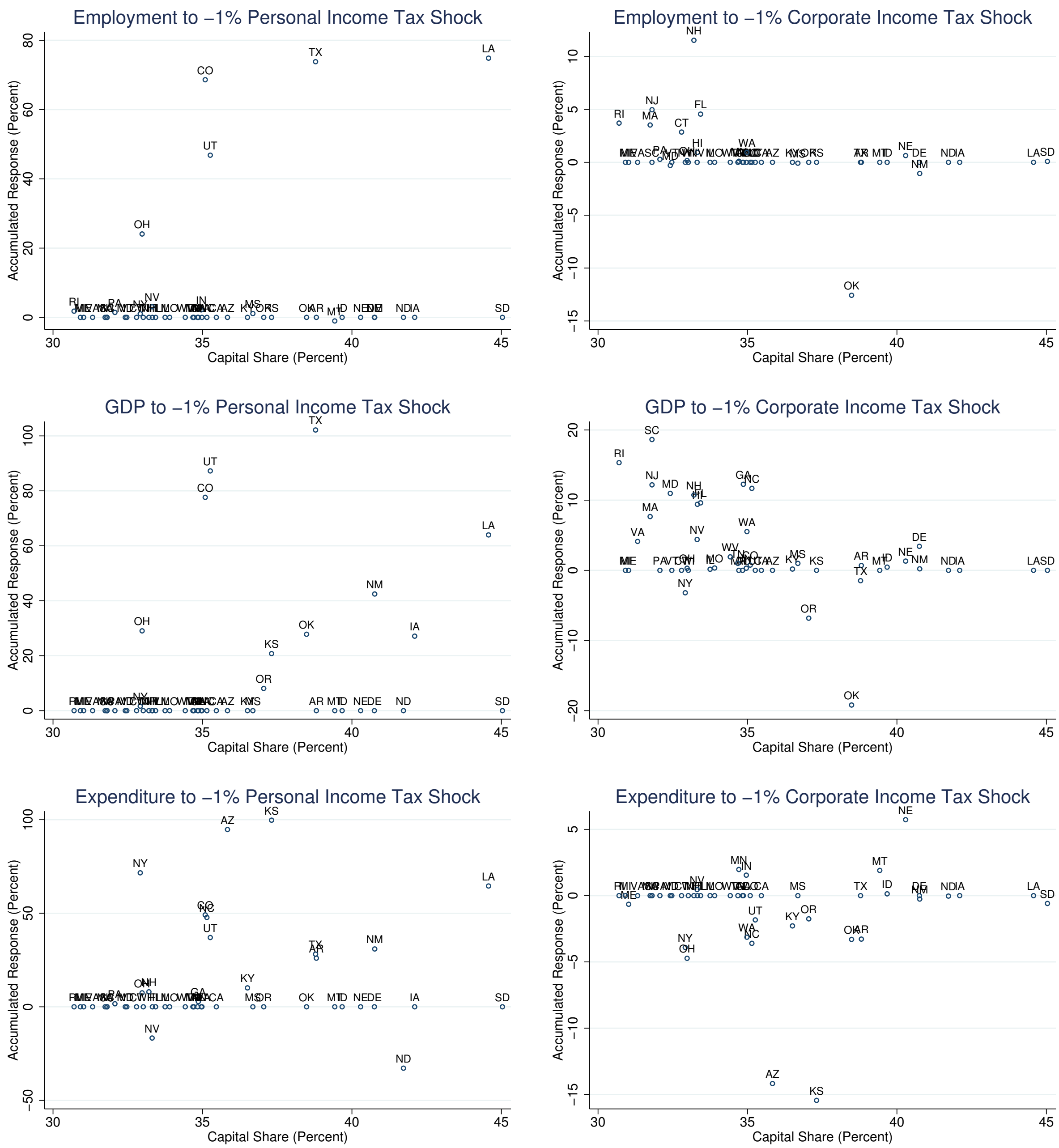


Figure 34: Cumulative Response by State (with Aggregate Variables)

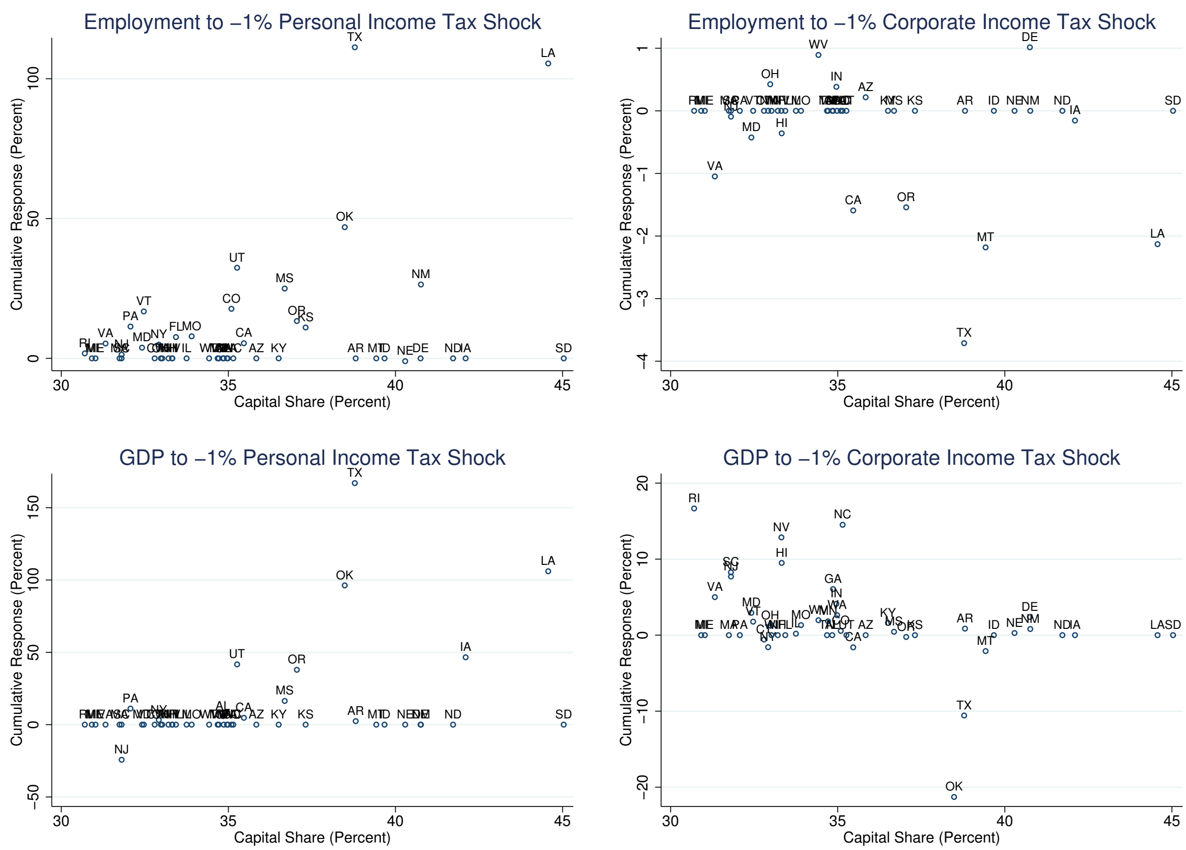


Table 16: Cumulative Responses on State Characteristics (Significance Level Not Considered)

	Panel A: All States				Panel B: Benchmark				Panel C: Using Tax Ratios			
	EMP-PIT	GDP-PIT	EMP-CIT	GDP-CIT	EMP-PIT	GDP-PIT	EMP-CIT	GDP-CI	EMP-PIT	GDP-PIT	EMP-CIT	GDP-CI
State PITR	-10.72*	-18.68	-1.551**	0.654	-4.051	1.466	-2.222***	-2.064**				
	(6.093)	(17.54)	(0.755)	(2.258)	(3.531)	(6.906)	(0.546)	(0.848)				
State CITR	-2.736	-1.152	0.284	-0.274	-3.854**	-6.297**	0.409	0.362				
	(2.249)	(5.266)	(0.275)	(0.754)	(1.716)	(2.403)	(0.256)	(0.454)				
Sales TR	-0.746	-10.51	-0.0616	1.393	2.856	1.153	-0.429	-0.155				
	(3.953)	(11.58)	(0.492)	(1.447)	(1.925)	(4.666)	(0.381)	(0.505)				
Capital Share	1.835	5.662**	-0.927***	-1.238***	1.138	5.039**	-0.867***	-1.106***	0.255	4.021**	-0.695***	-0.943***
	(1.552)	(2.724)	(0.197)	(0.390)	(1.433)	(2.003)	(0.192)	(0.292)	(1.470)	(1.833)	(0.168)	(0.264)
PIT/T									-0.546	-0.286	-0.0976*	-0.0680
									(0.358)	(0.538)	(0.0509)	(0.0825)
CIT/T									-2.618	-5.007**	0.614**	0.659
									(1.621)	(2.055)	(0.259)	(0.433)
Sales/T									0.114	-0.176	0.0643	0.153
									(0.356)	(0.576)	(0.0723)	(0.113)
Constant	-3.906	-79.82	37.78***	42.94**	-4.854	-124.8	38.17***	47.64***	30.14	-79.48	24.70***	31.91**
	(65.25)	(136.8)	(8.406)	(17.80)	(53.99)	(78.60)	(7.363)	(10.10)	(69.76)	(86.25)	(8.114)	(12.40)
N	50	50	50	50	48	48	48	48	48	48	48	48
adj. R^2	0.294	0.315	0.363	0.274	0.208	0.262	0.355	0.230	0.153	0.225	0.364	0.271

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.3 Additional Results for One Sector Models

Here we present and discuss the impulse responses from a variety of one sector models which we discussed in Section **??**. As we discussed there, the details of the models differ but the end result is the same. In each case the structure of the model does not change the basic result that the cumulative output response to a corporate tax cut is larger with a larger capital's share of income, which is counter to our empirical results.

Figure 35 considers two parameterizations of a standard real business cycle model with government spending, proportional taxes on capital and labor, and lump sum taxes which ensure the government's budget is balanced. In particular, we consider a standard Cobb-Douglas production function (with varying α) and assume a representative household has additively separable preferences:

$$u(C, N) = \log C - \frac{N^{1+\eta}}{1+\eta}.$$

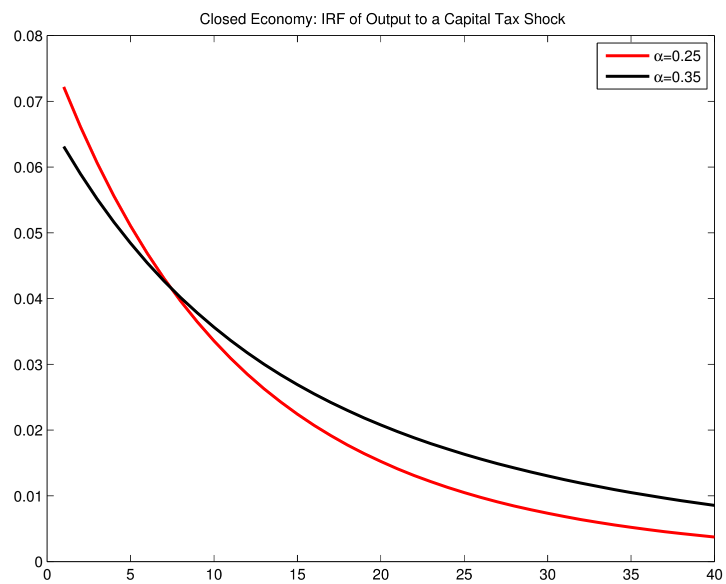
We suppose that the corporate or capital income tax is time-varying and follows the standard auto-regression:

$$\tau_{t+1} = \rho\tau_t + \varepsilon_{t+1}$$

While states are clearly not independent, closed economies, this model provides a useful benchmark. As we see in Figure 35, on impact the response of output is larger with a smaller capital's share α. This is largely due to the higher wages which accompany the tax cut and have a larger impact initially in a more labor-intensive economy. However as the capital stock grows over time, the response of the more capital intensive economy remains higher and comes to dominate. The cumulative response, which we focus on above, is thus higher with a greater capital's share.

We find much the same picture if instead of a closed economy, we suppose that each state is a small open economy. Here we focus on a case in which the state taxes national interest rates, which are determined as in a closed economy as above, as exogenous. In addition, we focus first on an incomplete markets case where capital markets are

Figure 35: Impulse response of output to a corporate tax shock in a closed economy model

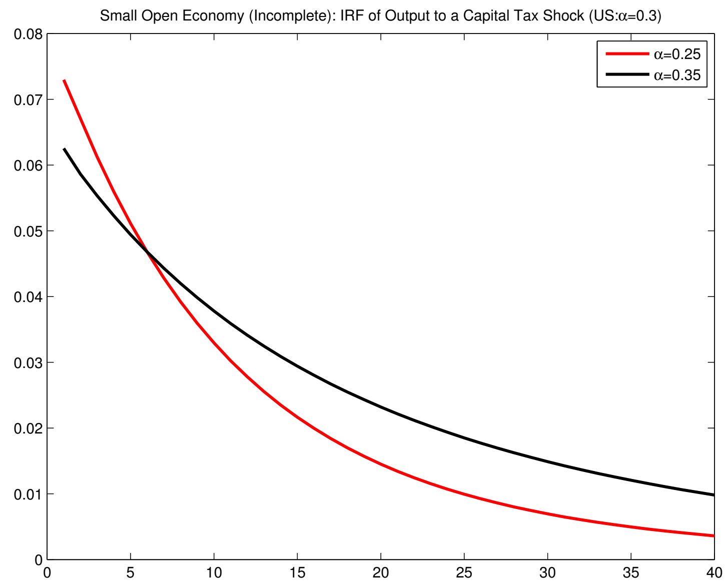


regional, with a bond being the only asset traded across state borders. To make the model stationary, we follow Schmitt-Grohé and Uribe (2003) and suppose that each state has an endogenous risk premium which depends on its net external debt. In this economy, we suppose that there is a federal corporate tax shock as above, which affects the national interest rates as well as directly affecting returns on capital in the state. Figure 36 shows that the responses to a corporate tax cut are nearly identical in this economy, and thus cannot explain the impulse responses we have estimated.

In the main text we considered a regional model, where Figure 22 shows that trade and factor reallocation matter, but they suggest larger cumulative responses with more capital intensity, counter to our empirical results.

Finally, we consider a three-region variation on the model of Nakamura and Steinsson (2014), who focus on the response across US states to a government spending shock. Relative to the models discussed so far, Nakamura and Steinsson (2014) introduce nominal frictions through monopolistic competition and sticky prices. They also more explicitly model trade, as consumers in each region consume a bundle of goods from other regions,

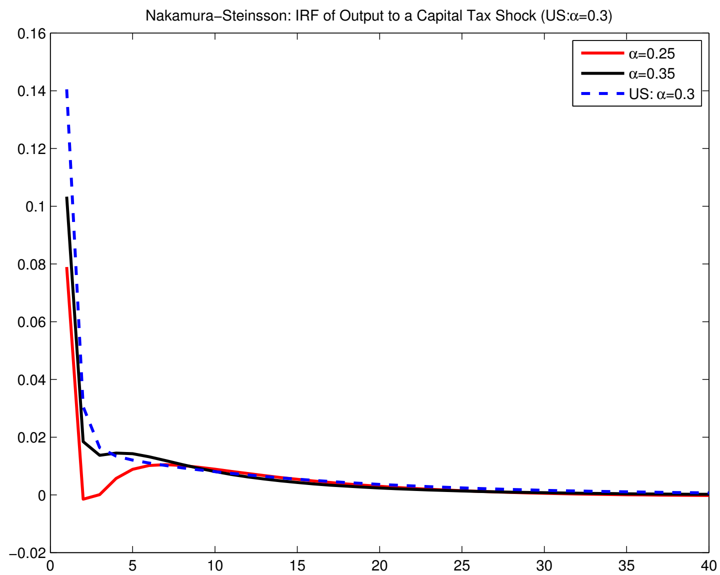
Figure 36: Impulse response of output to a corporate tax shock in a small open economy model with incomplete markets



which are imperfect substitutes. In addition, although most of their paper focuses on a model without capital, they show that introducing firm-specific capital with investment adjustment costs preserves their main conclusions, and in particular allows them to match the regional government spending multipliers that they estimate in their empirical work. Relative to Nakamura and Steinsson (2014), we introduce capital taxation and a third region, as in our simpler model above.

Figure 37 provides the results. Rather than prolonging the impact, the frictions in the model enhance the initial responses to the tax cut, but the effects fade away rather quickly. In addition, as in our other settings, the more capital-intensive region has a larger output response. We only show the responses for one specification of the model, which takes the baseline parameterization of Nakamura and Steinsson (2014). However the same qualitative results obtained in different parameterizations which varied the importance of the real and nominal frictions. Thus adding explicit trade and frictions do not seem sufficient to overturn the long-run implications of ours simpler models. Although this model can explain estimated government spending multipliers, it cannot

Figure 37: Impulse response of output to a corporate tax shock in a three region Nakamura-Steinsson model with complete markets



(at least in this form) explain the differential responses of states to federal tax shocks that we highlighted above.

Bibliography

Adão, R., C. Arkolakis, and F. Esposito (2019). “Spatial Linkages, Global Shocks, and Local Labor Markets: Theory and Evidence”. *NBER Working Paper*.

Amir-Ahmadi, P., C. Matthes, and M.-C. Wang (2016). “Drifts and Volatilities Under Measurement Error: Assessing Monetary Policy Shocks Over the Last Century”. *Quantitative Economics 7*(2), 591–611.

Aruoba, S. B., F. X. Diebold, J. Nalewaik, F. Schorfheide, and D. Song (2016). “Improving GDP Measurement: A Measurement-Error Perspective”. *Journal of Econometrics 191*(2), 384–397.

Asdrubali, P., B. E. Sørensen, and O. Yosha (1996). “Channels of Interstate Risk Sharing: United States 1963–1990”. *The Quarterly Journal of Economics 111*(4), 1081–1110.

Athanasoulis, S. G. and E. v. Wincoop (2001). “Risk Sharing Within the United States: What Do Financial Markets and Fiscal Federalism Accomplish?”. *Review of Economics and Statistics 83*(4), 688–698.

Backus, D. K., P. J. Kehoe, and F. E. Kydland (1992). “International Real Business Cycles”. *Journal of Political Economy 100*(4), 745–775.

Backus, D. K. and G. W. Smith (1993). “Consumption and Real Exchange Rates in Dynamic Economies with Non-Traded Goods”. *Journal of International Economics 35*(3-4), 297–316.

Barro, R. J. and J. Furman (2018). “Macroeconomic Effects of the 2017 Tax Reform”. *Brookings Papers on Economic Activity 2018*(1), 257–345.

Beraja, M. (2019). “Counterfactual Equivalence in Macroeconomics”. *cript*.

Beraja, M., A. Fuster, E. Hurst, and J. Vavra (2019). “Regional Heterogeneity and the Refinancing Channel of Monetary Policy”. *The Quarterly Journal of Economics 134*(1), 109–183.

Beraja, M., E. Hurst, and J. Ospina (2019). “The Aggregate Implications of Regional Business Cycles”. *Econometrica*, forthcoming.

Berger, D. W., L. Bocola, and A. Dovis (2019). “Imperfect Risk-Sharing and the Business Cycle”. *NBER Working Paper*.

Blanchard, O. and R. Perotti (2002). “An Empirical Characterization of the Dynamic Effects of Changes in Government Spending and Taxes on Output”. *The Quarterly Journal of Economics 117*(4), 1329–1368.

Blanchard, O. J. and L. F. Katz (1992). “Regional Evolutions”. *Brookings Papers on Economic Activity 1992*(1), 1–75.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2018). “Really Uncertain Business Cycles”. *Econometrica 86*(3), 1031–1065.

Blundell, R. and S. Bond (1998). “Initial Conditions and Moment Restrictions in Dynamic Panel Data Models”. *Journal of Econometrics 87*(1), 115–143.

Blundell, R., L. Pistaferri, and I. Preston (2008). “Consumption Inequality and Partial Insurance”. *American Economic Review 98*(5), 1887–1921.

Caliendo, L., F. Parro, E. Rossi-Hansberg, and P.-D. Sarte (2018). “The Impact of Regional and Sectoral Productivity Changes on the U.S. Economy”. *The Review of Economic Studies 85*(4), 2042–2096.

Chodorow-Reich, G. (2019). "Geographic Cross-Sectional Fiscal Spending Multipliers: What Have We Learned?". *American Economic Journal: Economic Policy 11*(2), 1–34.

Christiano, L. J., M. Eichenbaum, and C. Evans (1996). "The Effects of Monetary Policy Shocks: Evidence from the Flow of Funds". *The Review of Economics and Statistics 78*(1), 16–34.

Christiano, L. J., M. Eichenbaum, and C. L. Evans (1999). "Monetary Policy Shocks: What Have We Learned and to What End?". *Handbook of Macroeconomics 1*, 65–148.

Cogley, T., T. J. Sargent, and P. Surico (2015). "Price-level uncertainty and instability in the United Kingdom". *Journal of Economic Dynamics and Control 52*, 1–16.

Cole, H. L. and M. Obstfeld (1991). "Commodity Trade and International Risk Sharing: How Much Do Financial Markets Matter?". *Journal of Monetary Economics 28*(1), 3–24.

Corsetti, G., L. Dedola, and S. Leduc (2008). "International Risk Sharing and the Transmission of Productivity Shocks". *The Review of Economic Studies 75*(2), 443–473.

Crucini, M. J. (1999). "On International and National Dimensions of Risk Sharing". *Review of Economics and Statistics 81*(1), 73–84.

Dávila, E. and T. Philippon (2017). "Incompleteness Shocks". *unpublished manuscript*.

Del Negro, M. (2002). "Asymmetric Shocks Among US States". *Journal of International Economics 56*(2), 273–297.

Desmet, K., D. K. Nagy, and E. Rossi-Hansberg (2018). "The Geography of Development". *Journal of Political Economy 126*(3), 903–983.

Desmet, K. and E. Rossi-Hansberg (2014). "Spatial Development". *American Economic Review 104*(4), 1211–43.

Devereux, M. B. and V. V. Hnatkovska (2019). "Borders and Nominal Exchange Rates in Risk-Sharing". *Journal of the European Economic Association*, forthcoming.

Dupor, B., M. Karabarbounis, M. Kudlyak, and M. S. Mehkari (2019). "Regional Consumption Responses and the Aggregate Fiscal Multiplier". *Federal Reserve Bank of San Francisco Working Paper 2018-04*.

Evers, M. P. (2015). "Fiscal Federalism and Monetary Unions: A Quantitative Assessment". *Journal of International Economics 97*(1), 59–75.

Farhi, E. and I. Werning (2016). "Fiscal Multipliers: Liquidity Traps and Currency Unions". In *Handbook of Macroeconomics*, Volume 2, pp. 2417–2492. Elsevier.

Farhi, E. and I. Werning (2017). "Fiscal Unions". *American Economic Review 107*(12), 3788–3834.

Fischer, G. (2017). "The US Unemployment Insurance, a Federal-State Partnership: Relevance for Reflections at the European Level". Technical report, IZA Policy Paper.

Fitzgerald, D. (2012). "Trade Costs, Asset Market Frictions, and Risk Sharing". *American Economic Review 102*(6), 2700–2733.

Gertler, M. and P. Karadi (2015). "Monetary Policy Surprises, Credit Costs, and Economic Activity". *American Economic Journal: Macroeconomics 7*(1), 44–76.

Giroud, X. and H. M. Mueller (2019). "Firms' Internal Networks and Local Economic Shocks". *American Economic Review 109*(10), 3617–49.

Giroud, X. and J. Rauh (2018). "State Taxation and the Reallocation of Business Activity: Evidence from Establishment-Level Data". *Journal of Political Economy*, forthcoming.

Guerrieri, V. and G. Lorenzoni (2017). "Credit Crises, Precautionary Savings, and the Liquidity Trap". *The Quarterly Journal of Economics 132*(3), 1427–1467.

Guvenen, F., S. Ozkan, and J. Song (2014). "The Nature of Countercyclical Income Risk". *Journal of Political Economy 122*(3), 621–660.

Harberger, A. (1962). "The Incidence of the Corporation Income Tax". *Journal of Political Economy 70*, 15–240.

Harberger, A. (1995). "The ABCs of Corporation Tax Incidence: Insights into the Open-Economy Case". In *Tax Policy and Economic Growth*. Washington, DC: American Council for Capital Formation.

Herkenhoff, K. F., L. E. Ohanian, and E. C. Prescott (2018). "Tarnishing the Golden and Empire States: Land-Use Restrictions and the US Economic Slowdown". *Journal of Monetary Economics 93*, 89–109.

Hoffmann, M. and I. Shcherbakova-Stewen (2011). "Consumption Risk Sharing over the Business Cycle: the Role of Small Firms' Access to Credit Markets". *Review of Economics and Statistics 93*(4), 1403–1416.

House, C. L., C. Proebsting, and L. L. Tesar (2018). "Quantifying the Benefits of Labor Mobility in a Currency Union". *NBER Working Paper*.

Hurst, E., B. J. Keys, A. Seru, and J. Vavra (2016). "Regional Redistribution through the US Mortgage Market". *American Economic Review 106*(10), 2982–3028.

Jappelli, T. and L. Pistaferri (2010). "The Consumption Response to Income Changes". *Annual Review of Econonmics 2*(1), 479–506.

Jappelli, T. and L. Pistaferri (2011). "Financial Integration and Consumption Smoothing". *The Economic Journal 121*(553), 678–706.

Jentsch, C. and K. Lunsford (2018). "The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States: Comment". *American Economic Review*, forthcoming.

Jones, C., V. Midrigan, and T. Philippon (2018). "Household Leverage and the Recession". *NBER Working Paper*.

Kaplan, G., B. Moll, and G. L. Violante (2018). "Monetary Policy According to HANK". *American Economic Review 108*(3), 697–743.

Kaplan, G. and G. L. Violante (2018). "Microeconomic Heterogeneity and Macroeconomic Shocks". *Journal of Economic Perspectives 32*(3), 167–94.

Kotlikoff, L. and L. H. Summers (1986). "Tax Incidence". In A. J. Auerbach and M. Feldstein (Eds.), *Handbook of Public Economics*, Volume 2. Amsterdam: North-Holland Press.

Krueger, D., K. Mitman, and F. Perri (2016). "Macroeconomics and Household Heterogeneity". In *Handbook of Macroeconomics*, Volume 2, pp. 843–921. Elsevier.

Krueger, D., F. Perri, L. Pistaferri, and G. L. Violante (2010). "Cross-Sectional Facts for Macroeconomists". *Review of Economic Dynamics 13*(1), 1–14.

Liu, C. and N. Williams (2018). "Implications of a Quarterly State-Level Dataset". *manuscript*.

Liu, C. and N. Williams (2019). "State-Level Implications of Federal Tax Policies". *Journal of Monetary Economics 105*, 74 – 90.

Lustig, H. and S. Van Nieuwerburgh (2010). "How Much Does Household Collateral Constrain Regional Risk Sharing?". *Review of Economic Dynamics 13*(2), 265–294.

McKay, A. (2017). "Time-Varying Idiosyncratic Risk and Aggregate Consumption Dynamics". *Journal of Monetary Economics 88*, 1–14.

McKay, A. and R. Reis (2016). "The Role of Automatic Stabilizers in the US Business Cycle". *Econometrica 84*(1), 141–194.

McMurry, J. and N. Williams (2018). "Capital and Productivity in U.S. States". *manuscript*.

Mertens, K. and M. O. Ravn (2013). "The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States". *American Economic Review 103*(4), 1212–47.

Mertens, K. and M. O. Ravn (2014). "A Reconciliation of SVAR and Narrative Estimates of Tax Multipliers". *Journal of Monetary Economics 68*, S1–S19.

Mertens, K. and M. O. Ravn (2018). "The Dynamic Effects of Personal and Corporate Income Tax Changes in the United Statess: Reply to Jentsch and Lunsford". *FRB of Dallas Working Paper*.

Mian, A., K. Rao, and A. Sufi (2013). "Household Balance Sheets, Consumption, and the Economic Slump". *The Quarterly Journal of Economics 128*(4), 1687–1726.

Mian, A. and A. Sufi (2014). "What Explains the 2007–2009 Drop in Employment?". *Econometrica 82*(6), 2197–2223.

Nakamura, E. and J. Steinsson (2014). "Fiscal Stimulus in a Monetary Union: Evidence from US Regions". *American Economic Review 104*(3), 753–92.

Nekarda, C. J. and V. A. Ramey (2011). "Industry Evidence on the Effects of Government Spending". *American Economic Journal: Macroeconomics 3*(1), 36–59.

Obstfeld, M. and K. Rogoff (2000). "The Six Major Puzzles in International Macroeconomics: Is There a Common Cause?". *NBER macroeconomics annual 15*, 339–390.

Parker, J. A. and A. Vissing-Jorgensen (2009). "Who Bears Aggregate Fluctuations and How?". *American Economic Review 99*(2).

Perri, F. and J. Steinberg (2012). "Inequality and Redistribution During the Great Recession". *Federal Reserve Bank of Minneapolis Economic Policy Paper 12-1*.

Ramey, V. A. (2016). "Macroeconomic Shocks and Their Propagation". In *Handbook of Macroeconomics*, Volume 2, pp. 71–162. Elsevier.

Randolph, W. C. (2006). *"International Burdens of the Corporate Income Tax"*. Congressional Budget Office Washington, DC.

Ravn, M. O. and V. Sterk (2017). "Job Uncertainty and Deep Recessions". *Journal of Monetary Economics 90*, 125–141.

Redding, S. J. and E. Rossi-Hansberg (2017). "Quantitative Spatial Economics". *Annual Review of Economics 9*, 21–58.

Reiter, M. (2009). "Solving Heterogeneous-Agent Models by Projection and Perturbation". *Journal of Economic Dynamics and Control 33*(3), 649–665.

Romer, C. D. and D. H. Romer (2004, September). "A New Measure of Monetary Shocks: Derivation and Implications". *American Economic Review 94*(4), 1055–1084.

Romer, C. D. and D. H. Romer (2010). "The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks". *American Economic Review 100*(3), 763–801.

Sala-i Martin, X. and J. Sachs (1991, October). "Fiscal Federalism and Optimum Currency Areas: Evidence for Europe From the United States". Working Paper 3855, National Bureau of Economic Research.

Schmitt-Grohé, S. and M. Uribe (2003). "Closing Small Open Economy Models". *Journal of International Economics 61*(1), 163–185.

Schorfheide, F. and D. Song (2015). "Real-Time Forecasting With a Mixed-Frequency VAR". *Journal of Business & Economic Statistics 33*(3), 366–380.

Sims, C. A. and T. Zha (1998). "Bayesian Methods for Dynamic Multivariate Models". *International Economic Review*, 949–968.

Storesletten, K., C. I. Telmer, and A. Yaron (2004). "Cyclical Dynamics in Idiosyncratic Labor Market Risk". *Journal of Political Economy 112*(3), 695–717.

Stumpner, S. (2019). "Trade and the Geographic Spread of the Great Recession". *Journal of International Economics 119*, 169 – 180.

Suárez Serrato, J. C. and O. Zidar (2016). "Who Benefits from State Corporate Tax Cuts? A Local Labor Markets Approach with Heterogeneous Firms". *American Economic Review 106*(9), 2582–2624.

Werning, I. (2015). "Incomplete Markets and Aggregate Demand". *NBER Working Paper*.

Wieland, J. F. and M.-J. Yang (2020). "Financial Dampening". *Journal of Money, Credit and Banking 52*(1), 79–113.

Winberry, T. (2018). "A Method for Solving and Estimating Heterogeneous Agent Macro Models". *Quantitative Economics 9*(3), 1123–1151.