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Risk Sharing Heterogeneity in the United States

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Abstract

Several studies document high risk sharing against output fluctuations in the United States. Building on these studies, this note documents substantial heterogeneity in interstate risk sharing between US states. Using a panel data set ranging from 1963 to 2013, aggregate and state-specific risk sharing profiles are estimated. Moreover, four distinct clusters of states, each characterized by a unique risk sharing profile emphasizing one specific consumption insurance channel, are derived. This note then shows that this heterogeneity in insurance levels and profiles is related to differences in state characteristics, such as the composition of state output, insurance opportunities, vulnerability to idiosyncratic shocks, and the capacity to finance countercyclical policies.

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1 Introduction

Risk sharing refers to the notion that individuals attempt to insure their consumption streams against adverse regional economic events. Insurance takes place across regions through various mechanisms. In a monetary union, the understanding of these mechanisms is essential to mitigate the vulnerability of regions to economic shocks when nominal price adjustments are not possible.

Literature building on the seminal contribution of Asdrubali et al. (1996) has developed a methodology to quantify the sources of insurance across regions. In particular, Asdrubali et al. (1996) propose a variance decomposition of regional output growth to estimate the contribution of various risk sharing channels to consumption insurance. Several studies utilize this framework to investigate risk sharing in the United States (see, for instance, Mélitz and Zumer, 1999), the Euro Area (e.g., Cimadomo et al., 2018), or OECD countries (such as Sørensen and Yosha, 1998). Moreover, the methodology has been augmented to examine the effects of several different variables on the extent of risk sharing. For instance, Kalemli-Ozcan et al. (2003) investigate the effects of industrial specialization, Demyanyk et al. (2007) the impact of banking deregulation, and Sørensen et al. (2007) the consequences of home bias in debt and equity holdings. This note contributes to this literature by estimating to which extent and why regions differ in insurance profiles. Using available panel data of the United States from 1963 to 2013, I report estimates for risk sharing heterogeneity between US states and further analyze potential determinants of this heterogeneity which have not yet been examined in the related literature. To the best of my knowledge, this note is also the first to report risk sharing heterogeneity based on state-specific estimations of insurance profiles.

Following the aforementioned literature, three channels of risk sharing are considered: an *income smoothing* channel, *federal transfers*, and a *consumption smoothing* channel. The empirical results derived in this note point to large but imperfect consumption insurance. Income and consumption smoothing play a decisive role, as they insulate 48% and 26.6% of state consumption against regional output fluctuations, respectively. Federal transfers across states also play a significant but less vital role, contributing 9.4%. These estimates provide an *aggregate* insurance profile.

In order to document the diversity of insurance profiles across US states, I augment the methodology provided by Asdrubali et al. (1996) and estimate state-specific risk sharing profiles. Based on these estimates, this note reports distinct clusters of states, each with a unique insurance profile. In particular, the analysis documents that states differ substantially along two dimensions: the magnitude of consumption insurance and the contribution of each risk sharing channel. The state-specific analysis shows that overall insurance ranges from 68.1% to full insurance. Grouping states based on their individual risk sharing profile, four distinctive clusters can be identified. One cluster displays an insurance profile similar to the aggregate average profile. The other clusters are characterized by an insurance profile that emphasizes one specific risk sharing channel: one cluster insures significantly more through income smoothing (67.9%), one through federal transfers (17.4%), and one through consumption smoothing (53%).

I then investigate state observables which might determine these distinctive profiles. The note shows that overall risk sharing is positively associated with lower economic activity at risk, better insurance opportunities, and lower shock persistence. Furthermore, the contribution of federal transfers is positively associated with higher unemployment rate volatility and consumption smoothing is negatively associated with state tax and expenditure limits and higher population poverty rates.

The note is organized as follows. Section 2 discusses aggregate risk sharing channels and introduces the application to the United States. Section 3 then investigates the heterogeneity of risk sharing profiles between US states, and Section 4 relates the observed insurance heterogeneity to different state characteristics. Section 5 concludes.

2 Measuring Aggregate Risk Sharing

2.1 Insurance Channels and Estimation Strategy

Asdrubali et al. (1996) develop a methodology to identify and quantify inter-regional insurance channels. Consider the following decomposition of gross state product *gsp* for a state i at time t:

$$gsp_{it} = \frac{gsp_{it}}{si_{it}} \frac{si_{it}}{dsi_{it}} \frac{dsi_{it}}{c_{it}} c_{it}, \tag{1}$$

where *si* is defined as state income, *dsi* as disposable state income, and c as state consumption. From this expression, one can retrieve the following three channels that contribute to insulating consumption against *gsp* fluctuations.

Income flows. While *gsp* measures goods and services produced within the geographical boundaries of a state, *si* includes income from non-domestic financial investment, e.g., dividend, interest, and rental payments across states. Ex ante, these returns from diversified capital holdings might buffer variations in *gsp*.

Federal transfers. The difference between *si* and *dsi* reflects interstate public net transfers, i.e., it refers to the extent of the insurance provided by federal taxes and transfers.

Consumption smoothing. Ex post, private and public state residents can save or dissave on credit markets to adjust consumption c to variations in income.

As an illustration, assume that changes in *si* perfectly offset changes in *gsp* and c is constant over time. In this example, income flows provide perfect insurance to consumption against fluctuations in state output.

The empirical estimation of the contribution of each channel relies on a decomposition of the cross-sectional variance in *gsp* given by equation (1). Omitting i and t,

$$\begin{aligned} var\left(\Delta log(gsp)\right) =& cov\left(\Delta log(gsp), \Delta log(gsp) - \Delta log(si)\right) \\ &+ cov\left(\Delta log(gsp), \Delta log(si) - \Delta log(dsi)\right) \\ &+ cov\left(\Delta log(gsp), \Delta log(dsi) - \Delta log(c)\right) \\ &+ cov\left(\Delta log(gsp), \Delta log(c)\right). \end{aligned} \tag{2}$$

Dividing each side by the variance of (log) *gsp* growth yields

$$1 = \beta_I + \beta_F + \beta_C + \beta_U. \tag{3}$$

In this expression, β_U is the *unsmoothed* share of *gsp* variations which translate into consumption fluctuations: perfect insurance corresponds to $\beta_U = 0$. The remaining coefficients are associated with the insurance contribution of income flows (β_I), federal transfers (β_F), and consumption smoothing (β_C). These coefficients are estimated by running panel regressions. Following Asdrubali et al. (1996), I estimate:

$$\Delta log\left(gsp_{i,t}\right) - \Delta log\left(si_{i,t}\right) = \mu_{I,t} + \beta_I \Delta log\left(gsp_{i,t}\right) + u_{i,I,t}, \tag{4}$$

$$\Delta log\left(si_{i,t}\right) - \Delta log\left(dsi_{i,t}\right) = \mu_{F,t} + \beta_F \Delta log\left(gsp_{i,t}\right) + u_{i,F,t}, \tag{5}$$

$$\Delta log\left(dsi_{i,t}\right) - \Delta log\left(c_{i,t}\right) = \mu_{C,t} + \beta_C \Delta log\left(gsp_{i,t}\right) + u_{i,C,t}, \tag{6}$$

$$\Delta log\left(c_{i,t}\right) = \mu_{U,t} + \beta_U \Delta log\left(gsp_{i,t}\right) + u_{i,U,t}. \tag{7}$$

where $\mu_{z,t}$ are time fixed effects[1], $u_{i,z,t}$ an error term, and $z \in \{I, F, C, U\}$ the respective risk sharing channel. Formally, β_z is the elasticity of an insurance channel (left-hand side) to variations in regional income[2] (right-hand side). Importantly, time fixed effects eliminate aggregate fluctuations, so that coefficients capture the regional consumption insurance to regional shocks. Idiosyncratic regional fluctuations account for around 50% of the total fluctuations in state output.[3]

2.2 Data

The estimation of equations (4) - (7) relies on a panel data set of *gsp*, *si*, *dsi*, and *c* for each US state (plus Washington, DC), at annual frequency, covering 1963 - 2013. For this analysis, I merge two data sets: Asdrubali et al. (1996) provide the data for 1963 - 1998, data from Alcidi et al. (2017) is used for the remaining time period 1999 - 2013. Both rely on the same data construction procedure suggested by Asdrubali et al. (1996). A detailed overview of this method can be found in Table A.1 in the appendix. Note that when discussing the results, I will show that merging the data sets is valid and does not bias the results. In short, the relevant panel variables are constructed as follows.
Gross state product is defined as the value added of all industries at the state level.
State income measures the sum of personal and public income. Personal income includes, for instance, wages, supplements, or dividend income. Public income consists of non-personal tax and interest income, minus public transfers.
Disposable state income is defined as state income plus federal transfers to private individuals and (state or local) governments. Federal (non-)personal taxes are deducted.
State consumption measures the sum of private and public consumption at the state level.

2.3 Results

Table 1 displays the estimates of equations (4) - (7). Column 2 shows that aggregate consumption insurance is imperfect but high: $1 - \beta_u = 84.1\%$ of *gsp* fluctuations do not translate into consumption fluctuations. Income and consumption smoothing channels provide the largest buffers against *gsp* fluctuations, while federal transfers across states contribute around 10%.[4]

[1]Note that the structure of the equations implies that time fixed effects sum up to 0, i.e., $\sum_z \mu_{z,t} = 0 \forall t$.

[2]Note that *gsp* is regarded as exogenous, as in Asdrubali et al. (1996). Thus, the forthcoming results should be interpreted as statistical rather than causal relationships. Asdrubali and Kim (2004) address this issue in more detail and endogenize the output process. Overall, their results are broadly in line with the literature assuming exogenous output processes.

[3]Formally, the regression

$$\Delta log\left(gsp_{i,t}\right) = \mu_t + u_{i,t},$$

filtering aggregate shocks from variations in state output, is associated with an R^2 of 0.49.

[4]These results are broadly in line with Asdrubali et al. (1996), who report a share of 39% income smoothing, 13% federal transfers, and 23% consumption smoothing between 1963 and 1990. They also tally with Alcidi et al. (2017), who report 47%, 8%, and 27%, respectively, between 1998 and 2013.

In order to ensure the validity of merging the data sets, I additionally report separate results for the corresponding time frames in columns 3 and 4. Clearly, the results do not differ significantly between data sets, neither in terms of the level of the insurance contribution of each channel, nor in terms of (clustering-robust) standard errors[5].

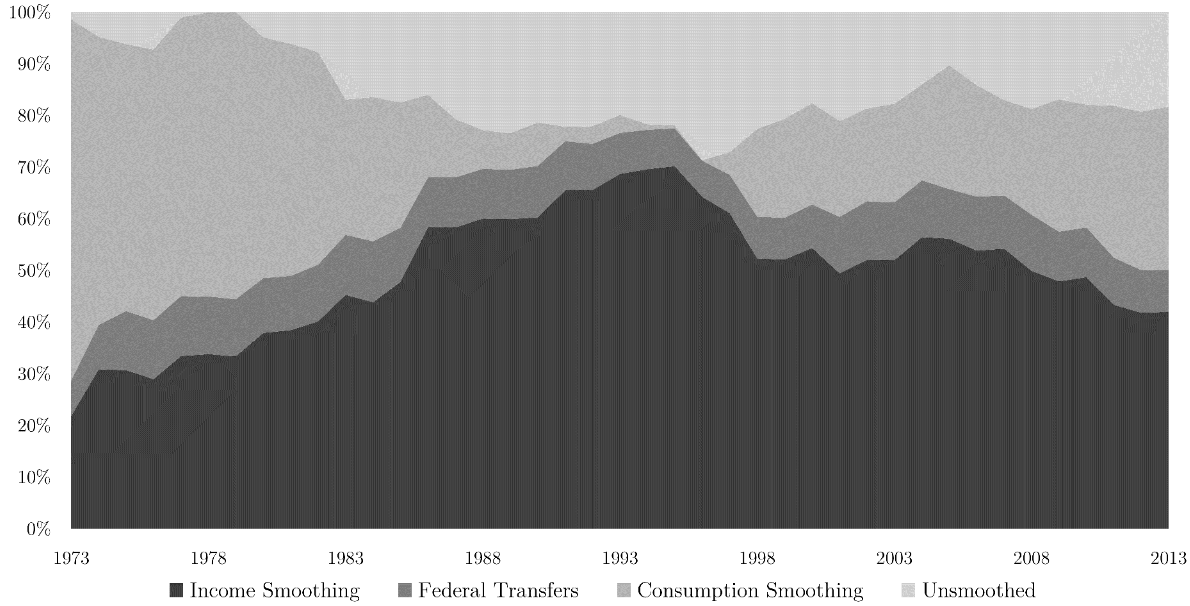
Table 1: Aggregate Risk Sharing in the United States

	1963-2013	1963-1998	1999-2013
Income Smoothing (β_I)	0.480***	0.482***	0.472***
	(0.06)	(0.08)	(0.06)
Federal Transfers (β_F)	0.094***	0.096***	0.089***
	(0.01)	(0.01)	(0.02)
Consumption Smoothing (β_C)	0.266***	0.268***	0.258***
	(0.06)	(0.08)	(0.06)
Unsmoothed (β_U)	0.159***	0.153***	0.181***
	(0.03)	(0.04)	(0.04)

Notes. The second column refers to the estimation results for all periods. Columns 3 and 4 report the estimates for the periods associated with each data set. Clustering-robust standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Note that the contribution of each insurance channel is not constant over time. As Figure 1 reports, there is substantial time variation when estimating risk sharing per year. Determination of the four coefficients relies on the estimation of equations (4) - (7) on a 10-year rolling window, i.e., on an estimation of the equations for each year from 1973 onwards, using observations from the previous 10 years.

Figure 1: Risk Sharing in the United States per Year



Notes. This figure reports the time variation in insurance channel estimates of a 10-year rolling window estimation of equations (4) - (7).

The results show an increasing role of income smoothing, a constant modest contribution

[5] Clustering-robust standard errors adjust for the 51 regions in the sample (50 states plus Washington, DC) and account for autocorrelation and heteroscedasticity.

of federal transfers (close to 10%), and strong variations in consumption smoothing. The unsmoothed share stabilizes around 20%.[6] These results tally with a similar analysis conducted by Asdrubali et al. (1996).

3 Measuring Heterogeneous Risk Sharing

3.1 Estimation Strategy

In order to shed light on potential heterogeneity between US states, I augment the system of equations (4) - (7) with state dummy variables to derive state-specific insurance profiles:

$$\Delta log\left(gsp_{i,t}\right) - \Delta log\left(si_{i,t}\right) = \mu_{I,t} + \beta_I \Delta log\left(gsp_{i,t}\right) + \sum\nolimits_j \theta_{i,j}\beta_{j,I}\Delta log\left(gsp_{j,t}\right) + u_{i,I,t}, \tag{8}$$

$$\Delta log\left(si_{i,t}\right) - \Delta log\left(dsi_{i,t}\right) = \mu_{F,t} + \beta_F \Delta log\left(gsp_{i,t}\right) + \sum\nolimits_j \theta_{i,j}\beta_{j,F}\Delta log\left(gsp_{j,t}\right) + u_{i,F,t}, \tag{9}$$

$$\Delta log\left(dsi_{i,t}\right) - \Delta log\left(c_{i,t}\right) = \mu_{C,t} + \beta_C \Delta log\left(gsp_{i,t}\right) + \sum\nolimits_j \theta_{i,j}\beta_{j,C}\Delta log\left(gsp_{j,t}\right) + u_{i,C,t}, \tag{10}$$

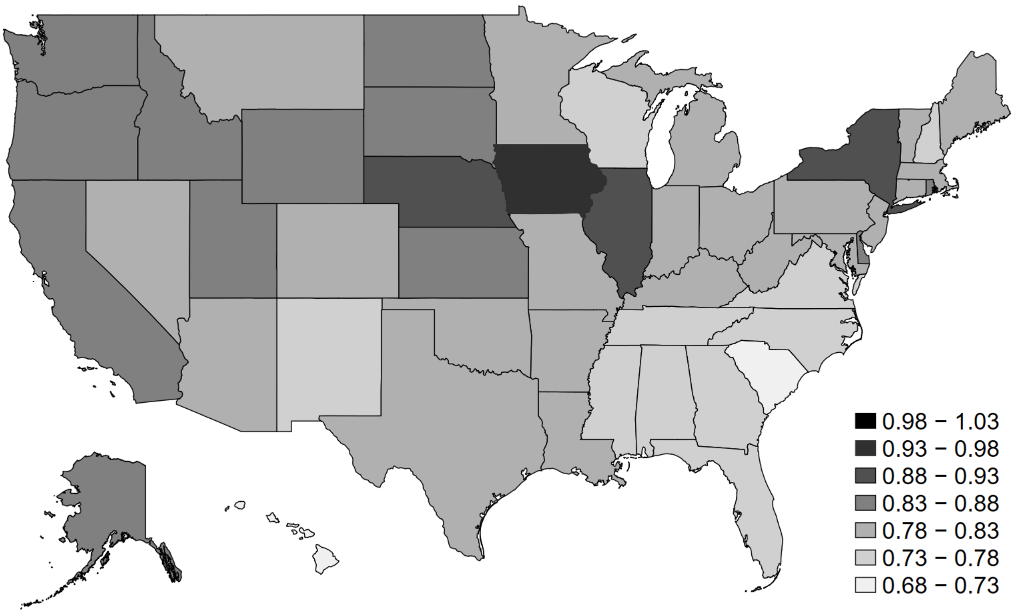
$$\Delta log\left(c_{i,t}\right) = \mu_{U,t} + \beta_U \Delta log\left(gsp_{i,t}\right) + \sum\nolimits_j \theta_{i,j}\beta_{j,U}\Delta log\left(gsp_{j,t}\right) + u_{i,U,t}, \tag{11}$$

where β_z is the risk sharing coefficient for the first state in the panel, i.e., Alabama, and $\theta_{i,j}$ is a dummy variable equal to 1 if $i = j$. In that case, $\beta_z + \beta_{i,z}$ is the risk sharing contribution of channel z to state i's consumption insurance.

3.2 Results

The estimation results suggest that there exists substantial heterogeneity in total insurance and large diversity of insurance profiles across US states.

Figure 2: State-Specific Consumption Insurance in the United States



Notes. This map reports the share $1 - \beta_U$ of insured output fluctuations for each state.

[6]Note that estimating aggregate risk sharing per decade confirms these results (see Table B.1 in the appendix).

The detailed results for each state can be found in Table C.1 in the appendix. Figure 2 reports the share of total consumption insurance for each state. Estimates range from a low of 68.1% in Hawaii to full insurance in Washington, DC.

Furthermore, there exists substantial heterogeneity with respect to the extent to which each risk sharing channel contributes to the insurance profile of individual states. Table 2 reports key statistics for all channels. In particular, income smoothing contributes to 60.5% of consumption insurance in Alaska and only to 27.5% in North Dakota. Federal transfers vary from 14.5% in Michigan to 6.1% in Washington, DC. Finally, consumption smoothing contributes to only 10.7% of insurance against *gsp* fluctuations in Hawaii but to 49.6% in North Dakota.

Table 2: State-Specific Risk Sharing in the United States Summary Statistics

	Minimum	Maximum	Average	Median	SD
Income Smoothing (β_I)	0.275	0.605	0.441	0.432	0.049
Federal Transfers (β_F)	0.061	0.145	0.109	0.110	0.016
Consumption Smoothing (β_C)	0.107	0.496	0.268	0.260	0.068
Unsmoothed (β_U)	-0.012	0.319	0.182	0.188	0.054

Notes. This table reports summary statistics of the state-specific insurance profiles estimated using equations (8) to (11). SD stands for standard deviation.

3.3 Risk Sharing Clusters

In order to identify representative risk sharing profiles, I use a k-means clustering procedure based on the state-specific insurance profiles. The clustering method allocates states into N clusters $\{c_j\}_{j=1}^N$ by minimizing the sum of squared differences within clusters:[7]

$$\min \sum_{j=1}^{N} \sum_{i \in c_j} dist(\gamma_j, \beta_i)^2, \tag{12}$$

where $\gamma_j = \{\gamma_{z,j}\}$ is the set of average risk sharing coefficients $\gamma_{z,j} = \frac{1}{\text{card}(c_j)} \sum_{i \in c_j} \beta_{z,i}$ within each cluster. Once states have been allocated into different clusters, I run the panel regressions outlined in equations (4)-(7) for each cluster to retrieve their respective risk sharing profiles.

I identify four distinct clusters, each characterized by a unique risk sharing profile.[8] Table 3 reports the cluster-specific insurance profiles and associated economic and demographic statistics. Clusters 1 to 3 are characterized by an insurance profile which emphasizes one specific channel: income smoothing (67.9% in Cluster 1), federal transfers (17.4% in Cluster 2), and consumption smoothing (53% in Cluster 3). Note that each of these clusters differs from all other clusters in their emphasized dimension at the 99% level. Cluster 4 gathers states with insurance profiles closest to the average profile reported in Table 1. Note that about 40% of states differ from the average risk sharing profile, constituting to roughly 30% of US *gdp* and population in 2013. Lastly, a measure for cluster compactness is reported, showing that the clustering method is successful in

[7]See Appendix D for more details on the implemented algorithm.

[8]Note that Washington, DC, is left out of the analysis because it has a unique insurance profile (see Table C.1 in the appendix for details).

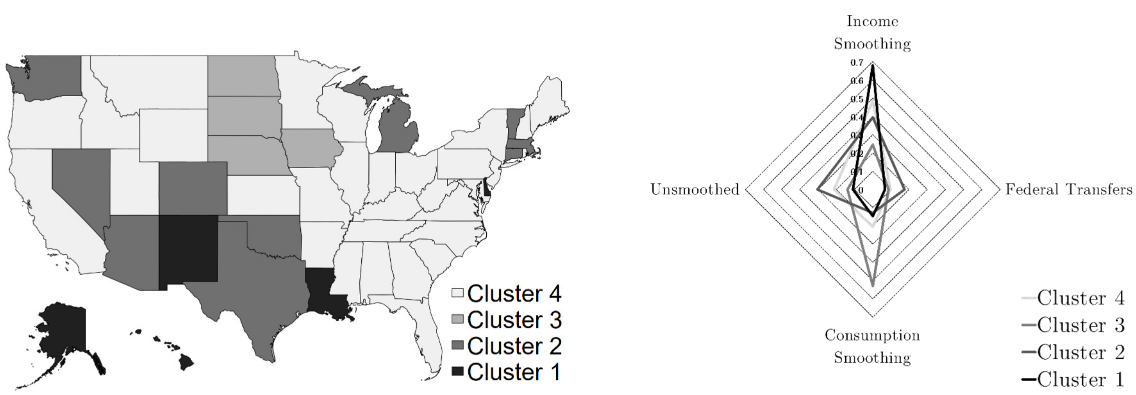
reducing the variance of state-specific insurance profiles within each cluster in comparison to the total variance across these profiles.

Table 3: Risk Sharing Clusters in the United States

Cluster 1 – Income Smoothing Cluster			
Insurance Profile		Descriptive Statistics	
Income Smoothing (β_I)	0.679*** (0.02)	Number of states	5
Federal Transfers (β_F)	0.067*** (0.01)	Population share	3.09%
Consumption Smoothing (β_C)	0.146** (0.06)	*gsp* share	3.13%
Unsmoothed (β_U)	0.109** (0.05)	Cluster compactness	63.51%
Cluster 2 – Federal Transfer Cluster			
Insurance Profile		Descriptive Statistics	
Income Smoothing (β_I)	0.394*** (0.04)	Number of states	10
Federal Transfers (β_F)	0.174*** (0.01)	Population share	23.03%
Consumption Smoothing (β_C)	0.129** (0.06)	*gsp* share	23.61%
Unsmoothed (β_U)	0.303*** (0.06)	Cluster compactness	9.32%
Cluster 3 – Consumption Smoothing Cluster			
Insurance Profile		Descriptive Statistics	
Income Smoothing (β_I)	0.245*** (0.07)	Number of states	4
Federal Transfers (β_F)	0.086*** (0.02)	Population share	2.06%
Consumption Smoothing (β_C)	0.530*** (0.05)	*gsp* share	2.19%
Unsmoothed (β_U)	0.139*** (0.03)	Cluster compactness	60.74%
Cluster 4 – Average Cluster			
Insurance Profile		Descriptive Statistics	
Income Smoothing (β_I)	0.484*** (0.04)	Number of states	31
Federal Transfers (β_F)	0.098*** (0.01)	Population share	71.63%
Consumption Smoothing (β_C)	0.204*** (0.03)	*gsp* share	68.99%
Unsmoothed (β_U)	0.213*** (0.05)	Cluster compactness	34.34%

Notes. Population share and *gsp* share refer to the relative population size and economic weight of each cluster in 2013. Cluster compactness refers to the variance of state-specific insurance profiles within each cluster relative to the total variance across clusters. Clustering-robust standard errors in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure 3: Cluster Composition and Insurance Profiles in the United States



(a) Cluster Composition (b) Cluster Insurance Profiles

Notes. Panel (a) illustrates the distribution of states in each cluster, Panel (b) provides a graphical overview of the insurance profiles of the clusters.

Figure 3 depicts the composition of each cluster and their insurance profiles graphically. Note that more details regarding the cluster composition can be found in Table C.1 in the appendix. This illustration further underscores the extent of heterogeneity between clusters and US states. Naturally, the results raise the questions of where this heterogeneity stems from and what accounts for the diversity of insurance profiles between states.

4 Determinants of Risk Sharing Heterogeneity

4.1 Estimation Strategy

In order to identify characteristics that are associated with state-specific insurance profiles, I follow Demyanyk et al. (2007) and Sørensen et al. (2007) by introducing an interaction term into equations (4)-(7). As an illustration, to assess how the overall insurance level is sensitive to variations in variable $x_{i,t}$, I estimate

$$\Delta log\,(c_{i,t}) = \mu_{U,t} + (\beta_U + \vartheta_U x_{i,t})\Delta log\,(gsp_{i,t}) + u_{i,U,t}, \tag{13}$$

where β_U is the average unsmoothed share and ϑ_U is the component associated with higher realizations of $x_{i,t}$, i.e., the sensitivity parameter.

Depending on the analyzed variable, the specification of $x_{i,t}$ can take two different forms:

$$x_{i,t} = \zeta_{i,t} - \bar{\zeta}_t, \tag{14}$$

or

$$x_{i,t} = D_{i,t} = \begin{cases} 1 & \text{if state i meets a certain condition in year t} \\ 0 & \text{otherwise.} \end{cases} \tag{15}$$

Equation (14) implies that any continuous variable $\zeta_{i,t}$ is corrected by the mean over all states $\bar{\zeta}_t$. The impact of binary state characteristics are measured by using dummy variables $D_{i,t}$ as defined in equation (15). I estimate ten relations of variables with risk sharing on all four dimensions, nine by using equation (14), one by using equation (15).

4.2 State Characteristics and Data

In this section, I briefly describe the seven considered state characteristics by commenting on the expected relationship between each variable and state insurance profiles as well as on the data (see Appendix E for details).

Composition of gsp – share of manufacturing sector. The level of risk sharing might be sensitive to the sectoral composition of *gsp*. For instance, one might expect that states with a relatively high manufacturing share have lower overall risk sharing due to the declining dynamism of manufacturing, i.e., $\vartheta_U > 0$. This hypothesis implies that states with a higher share of economic activity at risk have lower insurance capacities. In terms of data construction, the manufacturing sector share is defined as the value added by this sector at the state level for the entire time frame.

Composition of gsp – share of service sector. In contrast to the previous hypothesis, I expect $\vartheta_U < 0$ due to the continuing increase in the importance of the service sector. The service sector share is defined as the value added by this sector at the state level for all years. Table E.1 in the appendix delivers further details.

Correlation of gsp growth with US gdp growth. States whose output processes are negatively associated with the aggregate output process potentially have better diversification opportunities. Thus, I expect $\vartheta_U > 0$, i.e., states in which the relationship is particularly negative are characterized by higher overall insurance. Both *gsp* and *gdp* are defined as the value added of all industries for all periods.

Autocorrelation of gsp growth. Following Blundell et al. (2008), who find that consumption insurance against permanent income shocks is lower than against transitory shocks at the household level, I expect states with higher autocorrelation of *gsp* to have a lower overall insurance level ($\vartheta_U > 0$). The autocorrelation ρ for each state is retrieved by running the following simple estimation:

$$\Delta log\left(gsp_{i,t}\right) = \rho_i \Delta log\left(gsp_{i,t-1}\right) + \epsilon_{i,t},$$

where $\epsilon_{i,t}$ is the error term.

Unemployment rate volatility. High state unemployment rate volatility implies a stronger reaction of the state's unemployment rate to shocks. Thus, I expect $\vartheta_F > 0$, i.e., federal insurance mechanisms (like unemployment benefits, for instance) play a more vital role when the relative unemployment rate volatility is high. The volatility is calculated on the basis of average yearly unemployment rates at the state level between 1976 and 2013.[9]

Poverty rate level. A state's poverty rate level is a potential indicator of the capacity of individuals to react ex post to idiosyncratic shocks. Hence, I expect $\vartheta_C < 0$, implying that a higher poverty rate limits state residents in their consumption smoothing capacity. The estimation is based on the yearly poverty rate at the state level between 1995 and 2013.[10]

Public revenue and spending restrictions. Similar to the hypothesis for the impact of the poverty rate at the individual level, public revenue and spending restrictions might constrain states in reacting ex post to shocks. Between 1978 and 2006, 31 states introduced either a revenue limit (tieing state revenue to some index, for instance, inflation), an expenditure limit (tieing state expenditures to similar types of indices), or limited appropriations to a percentage of revenue estimates (tieing appropriations to a revenue forecast). A detailed overview can be found in Table E.2 in the appendix.

4.3 Results

Using the structure given by equation (15) to estimate the sensitivity of states' risk sharing profiles to the introduction of public revenue and spending restrictions and equation (14) for all other variables, I estimate the sensitivity parameter for each state characteristic as illustrated by equation (13) for all four channels. The findings are presented in Table 4. States where manufacturing contributes to a higher share of output have a higher unsmoothed share: an increase in the relative share of manufacturing in *gsp* by 1 percentage point decreases the consumption insurance level by 0.261 percentage points. This supports the hypothesis that states with a higher share of economic activity at risk have lower insurance capacities. Correspondingly, the sensitivity parameter of the unsmoothed share with respect to the service sector is negative. However, this estimate

[9]Note that the US Department of Labor only publishes state unemployment rates from 1976 onwards.

[10]Note that the US Census Bureau only publishes state poverty rates from 1995 onwards.

Table 4: Determinants of Risk Sharing Heterogeneity in the United States

Variable	ϑ_I	ϑ_F	ϑ_C	ϑ_U
Composition of gsp				
Manufacturing	-0.101	0.054	-0.214	0.261^{**}
	(0.13)	(0.03)	(0.18)	(0.12)
Services	-0.255^{**}	0.146^{***}	0.234	-0.124
	(0.12)	(0.04)	(0.16)	(0.12)
Correlation of *gsp* with US *gdp*	-0.068	0.052^{***}	-0.109	0.125^{**}
	(0.13)	(0.02)	(0.14)	(0.06)
Autocorrelation of *gsp* Growth	0.064	0.012	-0.165^{***}	0.089^{**}
	(0.06)	(0.01)	(0.06)	(0.04)
Unemployment Rate Volatility	0.017	0.015^{**}	-0.019	-0.013
	(0.02)	(0.007)	(0.01)	(0.01)
Poverty Rate Level	1.251^{***}	-0.164	-1.302^{**}	0.215
	(0.38)	(0.22)	(0.62)	(0.42)
Public Revenue and Spending Restrictions				
All Limits	0.088^{*}	-0.002	-0.083^{**}	-0.003
	(0.05)	(0.01)	(0.04)	(0.02)
Limited Appropriations	0.043	-0.024^{***}	-0.050	0.031
	(0.03)	(0.01)	(0.04)	(0.03)
Revenue Limit	-0.018	0.027^{**}	-0.007	-0.002
	(0.03)	(0.01)	(0.05)	(0.03)
Expenditure Limit	0.098^{*}	-0.003	-0.085^{**}	-0.011
	(0.06)	(0.01)	(0.04)	(0.02)

Notes. Data gathered and constructed as described in Section E in the appendix. Clustering-robust standard errors in parentheses. ${}^{*}p < 0.1$, ${}^{**}p < 0.05$, ${}^{***}p < 0.01$.

is not significantly different from 0. Moreover, the overall level of risk sharing is positively associated with higher negative correlations of *gsp* growth with US *gdp* growth: a decrease of the relative correlation by 0.1 increases the overall level of insurance by 1.25 percentage points. The results suggest that this higher level is achieved through both higher income and consumption smoothing. However, the estimates for these two coefficients are not significantly different from 0. Moreover, when shocks to state output are more persistent, insurance opportunities decrease and the overall insurance level is lower. The loss in insurance capacities primarily results from a decrease in consumption smoothing.

Furthermore, we find that risk sharing through federal transfers is positively associated with higher unemployment rate volatility, i.e., with unemployment rates that are very sensitive to shocks. An increase in relative volatility by 1 is associated with an increase in insurance through federal transfers of 1.5 percentage points.

Lastly, the results suggest that consumption smoothing is negatively associated with tax or expenditure limits for states and higher poverty rates. Tax and expenditure limits constrain states in financing countercyclical policies, higher poverty rates reflect low opportunities for individuals to do so. Overall, the introduction of a public revenue or spending restriction decreases a state's capacity to react ex post to idiosyncratic shocks by 8.3 percentage points. Interestingly, this effect is driven by states that introduced expenditure limits rather than revenue limits or states that limited appropriations. At the individual level, a relative increase in the poverty rate by 1 percentage point decreases consumption smoothing by 1.3 percentage points.

5 Conclusion

This note presents novel findings on substantial risk sharing heterogeneity between US states. In particular, by estimating state-specific risk sharing profiles and identifying four unique clusters, I show that states differ along two dimensions: the extent of overall insurance and the contribution of each risk sharing channel. Potential determinants of this heterogeneity are shown to be the composition of *gsp*, insurance opportunities of states, vulnerability to idiosyncratic shocks, or the capacity to finance countercyclical policies (by both individuals and states). Clearly, this is not an extensive list. There is a multitude of other state or individual characteristics that might play a role in explaining risk sharing heterogeneity. Moreover, this note invites to further deepen the understanding of heterogeneity in risk sharing. Naturally, the examination of insurance heterogeneity is not constrained to analyses between states but extends to investigations at the county or individual level. The analysis can also be extended by using dynamic econometric models (as in Asdrubali and Kim, 2004) to estimate risk sharing heterogeneity. While it seems intuitive that the presented results qualitatively apply to this dynamic perspective, empirical evidence is necessary to further underscore the relevance of heterogeneity in risk sharing.

References

Alcidi, C., P. D'Imperio, and G. Thirion (2017). "Risk-sharing and consumption-smoothing patterns in the US and the Euro Area: A comprehensive comparison". *CEPS Working Paper No 2017/04*.

Asdrubali, P. and S. Kim (2004). "Dynamic risksharing in the United States and Europe". *Journal of Monetary Economics 51*(4), 809–836.

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.

Blundell, R., L. Pistaferri, and I. Preston (2008). "Consumption inequality and partial insurance". *American Economic Review 98*(5), 1887–1921.

Cimadomo, J., S. Hauptmeier, A. A. Palazzo, and A. Popov (2018). "Risk sharing in the Euro Area". *ECB Economic Bulletin 3*, 85–98.

Demyanyk, Y., C. Ostergaard, and B. E. Sørensen (2007). "U.S. banking deregulation, small businesses, and interstate insurance of personal income". *The Journal of Finance LXII*(6), 2763–2801.

Kalemli-Ozcan, S., B. E. Sørensen, and O. Yosha (2003). "Risk sharing and industrial specialization: Regional and international evidence". *American Economic Review 93*(3), 903–918.

Mélitz, J. and F. Zumer (1999). "Interregional and international risk-sharing and lessons for EMU". *Carnegie-Rochester Conference Series on Public Policy 51*, 149–188.

National Conference of State Legislatures (2010). "State tax and expenditure limits". https://www.ncsl.org/research/fiscal-policy/state-tax-and-expenditure-limits-2010.aspx. Online; accessed 14-07-2021.

Sørensen, B. E., Y.-T. Wu, O. Yosha, and Y. Zhu (2007). "Home bias and international risk sharing: Twin puzzles separated at birth". *Journal of International Money and Finance 26*(4), 587–605.

Sørensen, B. E. and O. Yosha (1998). "International risk sharing and European monetary unification". *Journal of International Economics 45*(2), 211–238.

Appendices

A Aggregate Data Construction

Table A.1: Aggregate Data Construction

Category	Sources
Gross State Product	Bureau of Economic Analysis (bea)
State Income	
State Personal Income	bea
+ Federal Non-personal Taxes and Contributions	US Budget and Government Finances
+ State and Local Non-personal Taxes	Government Finances and bea
+ Interest on State and Local Funds	Government Fiances
− Direct Transfers (Federal and State)	bea
where	
Federal Non-personal Taxes and Contributions =	
Federal Corporate Income Taxes	United States Budget
+ Tobacco Taxes	United States Budget
+ Miscellaneous Taxes and Other Excise Taxes	United States Budget
+ Social Security Contributions	United States Budget
+ Unemployment Insurance Taxes	Government Finances
and where	
State and Local Non-personal Taxes =	
State and Local Tax Revenue	Government Finances
- State and Local Personal Taxes	bea
and where	
Interest on State and Local Funds =	
Interest on Insurance Trust Funds	Government Finances
+ Interest on State Miscellaneous Funds	Government Finances
+ Interest on Local Insurance Trust Funds	Government Finances
+ Interest on Local Miscellaneous Funds	Government Finances
- Interest on State Unemployment Deposits at the Treasury	Government Finances
Disposable State Income	
State Income	
+ Federal Grants to State Governments	United States Statistical Abstract
+ Federal Transfers to Individuals	bea and US Statistical Abstract
− Federal Non-personal Taxes and Contributions	US Budget and Government Finances
− Federal Personal Taxes	bea
where	
Federal Transfers to Individuals =	
OASDI Payments	bea
+ Railroad Retirement and Disability Payments	bea
+ Federal Civilian Employee Retirement Payments	bea
+ Military Retirement Payments	bea
+ Workers' Compensation	bea
+ Supplemental Social Security	bea
+ Food Stamps	bea

+ Other Federal Income Maintenance	bea
+ Unemployment Insurance Benefits	bea
+ Veterans Benefits	bea
+ Federal Education and Training Payments	bea
+ Federal Payments to Nonprofit Institutions	bea
+ Total Medical Payments	bea
- Medicaid Payments	United States Statistical Abstract
State Consumption	
Retail Sales (Rescaled) (1963-1996),	Sales & Marketing Management (1963-1996),
Private Consumption (1997-2013)	bea (1997-2013)
+ State and Local Government Consumption	Government Finances
where	
State and Local Government Consumption =	
State and Local Government Expenditure	Government Finances
- State and Local Transfers	
where	
State and Local Transfers =	
Direct Transfers	bea
- Federal Direct Transfers	bea

Notes. Construction of data as in Asdrubali et al. (1996).

B Risk Sharing in the United States per Decade

As Table B.1 reports, there is substantial time variation when estimating risk sharing per decade. The contribution of the income smoothing channel increases over time, federal transfers contribute close to 10% in most subperiods, and consumption smoothing varies strongly between 8.4% and 46.6%. The unsmoothed share stabilizes around 20% from 1981 onwards.

Table B.1: Risk Sharing in the United States per Decade

	1963-1970	1971-1980	1981-1990	1991-2000	2001-2010	2004-2013
Income Smoothing (β_I)	0.296***	0.379***	0.603***	0.543***	0.487***	0.419***
	(0.04)	(0.07)	(0.11)	(0.06)	(0.05)	(0.06)
Federal Transfers (β_F)	0.061***	0.106***	0.100***	0.083***	0.096***	0.080***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Consumption Smoothing (β_C)	0.343***	0.466***	0.084	0.196**	0.237***	0.317***
	(0.09)	(0.12)	(0.07)	(0.09)	(0.07)	(0.07)
Unsmoothed (β_U)	0.300***	0.05	0.214***	0.177***	0.180***	0.183***
	(0.09)	(0.05)	(0.06)	(0.06)	(0.03)	(0.05)

Notes. Estimates using equations (4) - (7) by decades. Clustering-robust standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C Sate-Specific Estimation

Table C.1 displays the state-specific estimation results. Note that, due to the introduction of state dummies, standard errors are high and most deviations from the first state in the panel (Alabama) are not statistically significant. Nevertheless, the results indicate substantial heterogeneity. Therefore, the cluster analysis is conducted. The estimation of the risk sharing profiles of these clusters display heterogeneity, which is also highly statistically significant.

Table C.1: State-Specific Risk Sharing in the United States

1964-2013

State	β_I	β_F	β_C	β_U	Cluster
Alabama	0.443 (0.04)	0.104 (0.01)	0.232 (0.08)	0.221 (0.07)	4
Alaska	0.605*** (0.04)	0.073** (0.02)	0.166 (0.08)	0.157 (0.07)	1
Arizona	0.437 (0.06)	0.122 (0.02)	0.262 (0.10)	0.180 (0.09)	2
Arkansas	0.399 (0.05)	0.108 (0.02)	0.316 (0.10)	0.176 (0.08)	4
California	0.459 (0.06)	0.124 (0.02)	0.281 (0.10)	0.137 (0.09)	4
Colorado	0.413 (0.06)	0.130 (0.02)	0.271 (0.10)	0.186 (0.09)	2
Connecticut	0.432 (0.05)	0.124 (0.02)	0.256 (0.10)	0.188 (0.09)	2
Delaware	0.571** (0.05)	0.079 (0.02)	0.186 (0.10)	0.164 (0.09)	1
Dist. of Col.	0.521 (0.05)	0.061** (0.02)	0.431** (0.09)	−0.012*** (0.08)	
Florida	0.402 (0.06)	0.114 (0.02)	0.259 (0.10)	0.225 (0.09)	4
Georgia	0.430 (0.05)	0.115 (0.02)	0.223 (0.10)	0.232 (0.09)	4
Hawaii	0.481 (0.05)	0.092 (0.02)	0.107 (0.10)	0.319 (0.09)	1
Idaho	0.436 (0.06)	0.113 (0.02)	0.313 (0.10)	0.139 (0.09)	4
Illinois	0.450 (0.06)	0.120 (0.02)	0.310 (0.11)	0.120 (0.09)	4
Indiana	0.472 (0.06)	0.104 (0.02)	0.237 (0.10)	0.187 (0.09)	4
Iowa	0.419 (0.05)	0.098 (0.02)	0.419* (0.10)	0.064* (0.09)	3
Kansas	0.443 (0.05)	0.112 (0.02)	0.296 (0.10)	0.150 (0.09)	4
Kentucky	0.422 (0.06)	0.110 (0.02)	0.260 (0.10)	0.208 (0.09)	4
Louisiana	0.516 (0.04)	0.098 (0.02)	0.195 (0.09)	0.190 (0.08)	1
Maine	0.424 (0.06)	0.107 (0.02)	0.262 (0.10	0.207 (0.09)	4
Maryland	0.455 (0.06)	0.100 (0.02)	0.254 (0.10)	0.191 (0.09)	4
Massachusetts	0.437 (0.05)	0.125 (0.02)	0.241 (0.10)	0.197 (0.09)	2
Michigan	0.429 (0.06)	0.145** (0.02)	0.234 (0.10)	0.192 (0.09)	2
Minnesota	0.412 (0.05)	0.111 (0.02)	0.288 (0.10)	0.188 (0.09)	4
Mississippi	0.422 (0.05)	0.095 (0.02)	0.259 (0.10)	0.225 (0.09)	4
Missouri	0.455 (0.06)	0.102 (0.02)	0.269 (0.10)	0.174 (0.09)	4
Montana	0.434 (0.06)	0.113 (0.02)	0.278 (0.10)	0.175 (0.09)	4
Nebraska	0.418 (0.05)	0.093 (0.02)	0.373 (0.10)	0.116 (0.09)	3
Nevada	0.430 (0.06)	0.139* (0.02)	0.244 (0.10)	0.187 (0.09)	2
New Hampshire	0.424 (0.05)	0.113 (0.02)	0.215 (0.10)	0.249 (0.09)	4
New Jersey	0.448 (0.06)	0.111 (0.02)	0.246 (0.10)	0.195 (0.09)	4
New Mexico	0.529 (0.05)	0.093 (0.02)	0.150 (0.10)	0.228 (0.09)	1
New York	0.467 (0.06)	0.101 (0.02)	0.318 (0.10)	0.114 (0.09)	4
North Carolina	0.402 (0.06)	0.111 (0.02)	0.228 (0.10)	0.258 (0.09)	4
North Dakota	0.275*** (0.05)	0.101 (0.02)	0.496*** (0.09)	0.128 (0.08)	3
Ohio	0.418 (0.06)	0.112 (0.02)	0.277 (0.10)	0.194 (0.09)	4
Oklahoma	0.429 (0.05)	0.135* (0.02)	0.233 (0.09)	0.203 (0.08)	2
Oregon	0.453 (0.06)	0.116 (0.02)	0.301 (0.10)	0.130 (0.09)	4
Pennsylvania	0.432 (0.06)	0.107 (0.02)	0.263 (0.10)	0.198 (0.09)	4
Rhode Island	0.442 (0.06)	0.105 (0.02)	0.292 (0.10)	0.161 (0.09)	4
South Carolina	0.420 (0.05)	0.106 (0.02)	0.179 (0.10)	0.295 (0.09)	4
South Dakota	0.355* (0.05)	0.092 (0.02)	0.421** (0.09)	0.131 (0.08)	3
Tennessee	0.419 (0.06)	0.101 (0.02)	0.252 (0.10)	0.228 (0.09)	4
Texas	0.457 (0.05)	0.121 (0.02)	0.234 (0.10)	0.188 (0.08)	2
Utah	0.458 (0.06)	0.122 (0.02)	0.272 (0.10)	0.148 (0.09)	4
Vermont	0.409 (0.06)	0.121 (0.02)	0.267 (0.10)	0.202 (0.09)	2
Virginia	0.419 (0.05)	0.108 (0.02)	0.233 (0.10)	0.239 (0.09)	4
Washington	0.423 (0.06)	0.138* (0.02)	0.300 (0.10)	0.139 (0.09)	2
West Virginia	0.428 (0.06)	0.112 (0.02)	0.247 (0.10)	0.213 (0.09)	4
Wisconsin	0.417 (0.06)	0.109 (0.02)	0.242 (0.10)	0.231 (0.09)	4

Wyoming	0.500 (0.05)	0.098 (0.02)	0.276 (0.09)	0.125 (0.08)	4

Notes. Standard Errors in Parentheses. Significance in terms of deviations from value of first state in panel (Alabama). $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

D K-Means Clustering

The k-means clustering algorithm performs the following steps:
(1.) pick arbitrary sets of average risk sharing coefficients γ_j
(2.) assign each state i to a cluster j as to minimize the associated increase in variance
(3.) given the allocation, compute the cluster mean γ_j
Repeat (2.) and (3.) until there is no reassignment of states across clusters that further reduces the objective function. Importantly, note that the procedure is implemented on standardized coefficients $\mathbb{E}[\beta] = 0$ and $Var[\beta] = 1$ to eliminate sorting weighted by relative size of insurance channels.

E Determinants of Risk Sharing Heterogeneity - Data Construction

Composition of gsp – manufacturing and services. The bea publishes the composition of gross state product for the whole considered time frame. In 1997, the measure of gsp was changed and consequently also the way components within gsp were reported. While there are no changes to the measures of the manufacturing sector, the composition of the reported service sector changes. Up to 1997, the bea reports a component of gsp called “service”. After 1997, however, this measure changes to “private service-providing industries”. In order to have a consistent measure, I add “retail trade”, “wholesale trade, and transportation” and “public utilities” to “services” between 1963 and 1996. From 1997 to 2013, “finance, insurance, or real estate services” are subtracted from the “private service-providing industries” measure. This ensures that a consistent measure over the entire time frame is used. Table E.1 summarizes the construction process.

Table E.1: Gross State Product Composition - Data Construction

Category	Sources
Manufacturing Sector	bea
Service Sector	
From 1963-1996:	
Services	bea
+ Retail Trade	bea
+ Wholesale Trade	bea
+ Transportation and Public Utilities	bea
From 1997-2013:	
Private Services Producing Industries	bea
- Finance, Insurance, Real Estate, Rental, and Leasing	bea

Notes. Data construction of manufacturing and service sector in order to get a consistent measure for the considered time frame.

Correlation of gsp with US gdp. The data for gsp and gdp are published by the bea for the entire considered time period.
Autocorrelation of gsp growth. Again, gsp data is drawn from the bea for all years.
Unemployment rate volatility. The state specific unemployment rates are published by the US Department of Labor from 1976 onwards on a monthly basis. I calculate and use the average unemployment rate for every year. The overall US unemployment rate is taken from the Current Population Survey, also using the average for every year.
Public revenue and spending restrictions. State tax and expenditure limits are published by the National Conference of State Legislatures (2010). Following their definition, states can operate under traditional limits or other limitations. Traditional limits include revenue limits (tieing state revenue to some index, for instance, inflation), expenditure limits (tieing state expenditures to similar types of indices), appropriations limited to a percentage of revenue estimates (tieing appropriations to a revenue forecast), or Hybrids (combining different aspects of the limits mentioned before). Other tax and expenditure limitations include voter approval requirements (implying that tax increases require voter approval) or supermajority requirements (implying a certain threshold of votes in the responsible government branches). Table E.2 shows in which year a state adopted a certain limit, if it was introduced.

Table E.2: Public Revenue and Spending Restrictions

State	Appropriations	Revenue	Expenditure
Alabama	-	-	-
Alaska	-	-	1982
Arizona	-	-	1978
Arkansas	-	-	-
California	-	-	1979
Colorado	-	-	1991
Connecticut	-	-	1991
Delaware	1978	-	-
Dist. of Col.	-	-	-
Florida	-	1994	-
Georgia	-	-	-
Hawaii	-	-	1978
Idaho	-	-	1980
Illinois	-	-	-
Indiana	-	-	2002
Iowa	1992	-	-
Kansas	-	-	-
Kentucky	-	-	-
Louisiana	-	-	1993
Maine	-	-	2005
Maryland	-	-	-
Massachusetts	-	1986	-
Michigan	-	1978	-
Minnesota	-	-	-
Mississippi	1982	-	-
Missouri	-	1980	-

Montana	-	-	1981*
Nebraska	-	-	-
Nevada	-	-	1979
New Hampshire	-	-	-
New Jersey	-	-	1990
New Mexico	-	-	-
New York	-	-	-
North Carolina	-	-	1991
North Dakota	-	-	-
Ohio	-	-	2006
Oklahoma	-	-	1985
Oregon	-	2000	-
Pennsylvania	-	-	-
Rhode Island	1992	-	-
South Carolina	-	-	1980
South Dakota	-	-	-
Tennessee	-	-	1978
Texas	-	-	1978
Utah	-	-	1989
Vermont	-	-	-
Virginia	-	-	-
Washington	-	-	1993
West Virginia	-	-	-
Wisconsin	-	-	2001
Wyoming	-	-	-

Notes. Appropriations, Revenue, and Expenditure denote the year in which that type of tax or expenditure limit has been introduced in a state, respectively. Cell with "-" indicate that a state has not introduced such a limit in the given time frame.* Montana introduced an expenditure limit only between 1981 and 2004.

Poverty rate level. The state specific and overall US poverty rate levels from 1995 onwards are taken from the Federal Reserve Bank of St. Louis, drawing from data of the US Census Bureau.