Bells in Space: The Spatial Dynamics of US Interpersonal and Interregional Income Inequality

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Abstract

Social and interregional inequality patterns across US states from 1929-2012 are analyzed using exploratory space-time methods. The results suggest complex spatial dynamics for both inequality series that were not captured by the stylized model of Alonso (1980). Interpersonal income inequalities of states displayed a U-shaped pattern ending the period at levels that exceeded the alarmingly high patterns that existed in the 1920s. Social inequality is characterized by greater mobility than that found for state per capita incomes. Spatial dependence is also distinct between the two series, with per capita incomes exhibiting strong global spatial autocorrelation, while state interpersonal income inequality does not. Local hot and cold spots are found for the per capita income series, while local spatial outliers are found for state interpersonal inequality. Mobility in both inequality series is found to be influenced by the local spatial context of a state.

1 Introduction

Through a synthesis of previous research on regional economic development, Alonso (1980) provided a stylized model of how to explore the relationships between the dynamics of five different aspects of economic development: [1] economic growth; [2] social inequality; [3] regional inequality; [4] geographical concentration of population; and [5] demographic transition. The bell analogy relates to the so-called inverted U pattern, posited by Kuznets (1955) for social, or personal income, inequality, and Williamson (1965) for regional inequality, in that the shape of the bell portrays the expected evolution of each type of inequality as an economic system develops. Alonso also suggested the bell-shaped curve gave good approximation to the evolution of the three other phenomena.

While immensely important for regional scientists, these bells leave the geographic dimensions of these dynamics largely untouched. These trajectories do tell us something about the dynamics of some overall, whole map, statistic, but they are silent on the spatial footprint of those dynamics. Although Alonso also argued that two of these phenomena, regional inequality and geographical concentration, were spatial in nature his definition of spatial is a limited one in that for both attributes the concentration, or inequality, is actually a summary measure of the values of those attributes and is invariant to the spatial distribution of the underlying phenomena across the units (i.e., states, counties, regions).

In this paper I revisit two of these five bells to consider the spatial dynamics of regional income inequality and interpersonal income inequality. Drawing on recently developed methods of exploratory space-time data analysis I first examine each series individually followed by a comparative analysis. Specific attention is given to the rate of mobility, or spatial change, in the inequality measure over time. Discrete Markov chains and their spatial extensions are applied to series for the US states over the period 1929-2012.

The remainder of the paper is organized as follows. I first discuss the motivation for focusing on a joint treatment of regional and interpersonal income inequality in Section 2. This is followed by a description of the data series and particular spatial analytics of the research design in Section 3. In Section 4 the results of the analysis are examined, and the paper concludes with an overview of the key findings and directions for future research.

2 Interpersonal and Interregional Income Inequality

This paper focuses on, and contrasts, patterns of two types of inequality, interpersonal and interregional, or what Alonso referred to as social and regional inequality, respectively. Both types of inequality have attracted enormous attention in large literatures.[1] However, these two literatures are largely independent. Alonso's reasoning some 35 years ago suggested that the two inequality series should be tied together. One of the main goals of this paper is to reconsider the two forms of inequality in tandem using the US experience as the empirical setting.

2.1 Interpersonal Inequality

In the US, the 1970s marked the end of a long period of declining income inequality that began during the 1940s. Initially the reversal was gradual, but beginning in the 1980s the increase in inequality accelerated. The nature of this shift has been rather dramatic and, unsurprisingly, has attracted much attention from both academics and policy makers (Galbraith, 2012; Noah, 2012; Stiglitz, 2012; Wilkinson and Pickett, 2006). Piketty and Saez (2013) note that one consequence of this rise in interpersonal US income inequality has been that the share of income going to individuals in the top percentile of the income distribution has more than doubled from just under 10 percent in the 1970s to over 20 percent in 2010. At the same time, more than 15 percent of US national income has shifted from individuals in the bottom 90 percent to those in the top decile of the distribution. The shift itself has also been particularly concentrated within the top decile, as more than 60 percent of US aggregate income growth between 1976 and 2007 has been absorbed by the top 1 percent of the distribution (Piketty and Saez, 2013, p. 458).

The use of metaphors to describe temporal patterns of aggregate interpersonal inequality continues in the modern literature as reflected in the arguments of Piketty and Saez (2006, p. 201) who note that:

> The overall pattern of the top decile share of the century is U-shaped.

[1]For overviews of the regional inequality literature see Rey and Janikas (2005), and for a survey of personal income inequality see Piketty and Saez (2013); Smeeding and Thompson (2011).

Of course they go on to note that this is not an *inverted-U*, and thus their finding is at odds with the stylized arguments of Kuznets (1955), and, I would add, Alonso.

A number of arguments have been put forth regarding the forces behind these personal income inequality dynamics in the US. Increasing international trade in the form of import competition over the past several decades has been linked to inequality, yet the estimates of trade's contribution to rising inequality has varied from highs of 50 percent (Wood, 1994), to lower shares of 20 (Leamer, 1994) to 10 percent (Krugman and Lawrence, 1993), with some studies finding no significant linkage between trade and inequality (Sachs et al., 1994). However, results in Rigby and Breau (2008) challenge the findings that trade has little impact on rising inequality, as their examination of the relationship at a finer sub-national spatial scale revealed a positive association between the growth of trade and wage inequality.

The impact of skill-biased technical change (SBTC) has been argued by some to be a significant factor being rising inequality. By increasing the demand for more highly educated labor, SBTC is said to put upward pressure on their wages and, conversely, downward pressure on the wages of less educated workers leading to a widening of wage inequality. Estimates of SBTC's contribution to rising inequality are on the order of 25-40 percent (Breau, 2007). In contrast Card and DiNardo (2002) suggest that SBTC is not a significant source of wage inequality increases in the US.[2]

In addition to trade and technological changes, a number of institutional sources of raising US income inequality have been put forth. Changes in the US tax system through the 1981 Economic Recovery and Taxation Act and the Tax Reform act of 1986 have resulted in increased regressivity of personal income taxes (Levy and Murnane, 1992, p. 1346). Similarly, corporate income taxes have declined from a high of 39.8 percent in the 1940's to 9.9 percent in 2012 (Stiglitz, 2014, p. 9) the benefits of which have disproportionately accrued to high income individuals.

Alongside changes in tax policies, Kristal (2013) argues that the decline in unionization, from a high of 24% in 1945 to under 8% by 2012, caused a decline in labor's share of national income resulting in increased inequality. Gordon (2014) estimates that declining unionization accounted for about a third of the increase in inequality in the 1980s and 1990s. Card and DiNardo (2002) point to a fall in the real value of the minimum wage in the US over

[2]It should be kept in mind that trade and technological change are not necessarily orthogonal so attempts at decomposing inequality rises to constituent forces should be viewed with caution.

the 1970-2000 period as explaining some 90% of the variation in the gap between the 90 and 10% wage percentiles.

These arguments concern the evolution of aggregate interpersonal inequality at the national level. There has been a smaller related research thread examining patterns at the subnational scale.[3] A number of studies have focused on the variation in interpersonal income inequality across regional economies in the US (Levernier et al., 1995; Partridge, 1997; Partridge et al., 1998; Panizza, 2002; Partridge, 2005; Frank, 2009). Changes in inequality at the subnational level have been associated with changes in demographic variables, such as immigration (Chakravorty, 1996; Nielsen and Alderson, 1997), household and gender composition (Madden, 2000; Essletzbichler, 2015), as well as industrial economic restructuring (Odland and Ellis, 2001), labor sorting (Moretti, 2013; Andersson et al., 2014), and exposure to international trade (Rodríguez-Pose, 2012).

Many times the question of interest is the impact of interpersonal inequality on the region's rate of economic growth. To the extent that inequality may have a negative impact on economic growth, spatial variations in interpersonal inequality may result in uneven regional growth. The evidence on this relationship is mixed across studies. Partridge (1997) finds a positive relationship between different measures of inequality and US state income growth. Using a different methodological framework, but similar data, Panizza (2002) finds no evidence of a positive relationship between changes in inequality and changes in growth. While these two studies employed data at 10-year intervals, Frank (2009) develops an annual series of state income inequality and finds a positive relationship between the top decile share of income in a state, and the state's economic growth. Additionally, the trends in inequality at the state level are found to mimic the overall trend in aggregate US inequality.

2.2 Interregional Inequality

The second of Alonso's five bells examined here concerns regional inequality. While interpersonal inequality focuses on the inequalities between individuals, interregional inequality is concerned with the inequalities between the average incomes of regions within a national system. Relative to the number of studies of regional interpersonal income inequality reviewed above, the literature on interregional income equality is considerably larger, dating

[3] As is well known, inequality in wealth distributions tends to be greater than income inequality. However, data constraints prohibit an examination of wealth inequality below the national scale in the US.

back to early work by Myrdal (1957); Easterlin (1960); Williamson (1965). This early work focused on the general empirical regularity that the level of inequality between regions in a national economy tended to display an inverted U pattern, increasing during early stages of national development but then declining as the economy reached high levels of development.

Since this early work, the number of studies of regional interregional inequality has exploded, and an overview of this work is beyond the current scope.[4] Broadly speaking, studies of interregional inequality can be placed into two groups based on the methodological approach adopted, those focusing on decompositions of regional inequality and those adopting a more confirmatory approach that subsumes interregional inequality within the question of regional income convergence.

The decomposition studies typically define a mutually exclusive and exhaustive partitioning of the individual economies into regions and then use this regionalization to separate total inequality into two components: interregional inequality and intraregional inequality. The former reflects the inequality due to the differences in the average group mean incomes, while the latter measures inequality between economies assigned to the same region. Work on the US has demonstrated that within-region inequality tends to be the larger of the two inequality components (Krugman, 1991; Fan and Casetti, 1994; Rey, 2004). This echoes similar findings from studies of other national systems (Shorrocks and Wan, 2005).

A slightly different perspective on interregional inequality can be seen in the work using finer spatial scales to measure inequality, and relating that to growth at the more aggregate level (Amos Jr., 1983, 1988; Janikas and Rey, 2005, 2008). For example, rather than measure interpersonal income inequality, interregional inequality between counties is used. Both sets of studies report a great deal of heterogeneity in the inequality-growth nexus across the states. Moreover, Janikas and Rey (2005) find that a very strong positive relationship between spatial clustering in state income levels and national economic growth in income takes on a different form at a lower spatial scale where a generally negative relationship holds between intrastate spatial clustering and state level income growth.

The second group of studies on interregional inequality is the vast literature on so called regional economic convergence (Rey and Le Gallo, 2009). Alternative types of convergence have been examined in the literature, with the most focus being on σ- and β-convergence. σ-convergence refers to a decline in the dispersion in the cross-sectional distribution of regional incomes

[4]For an overview see Rey and Janikas (2005).

over time. β-convergence is tied to neoclassical growth models suggesting that the growth rate in a region's income is a positive function of the distance from its steady-state. Empirical analysis of β convergence typically specifies income growth rates as a function of initial incomes and variables that condition for the steady state of each region.

For the US a number of studies have found general long-run evidence for both σ (Rey and Dev, 2006; Young et al., 2008) and β convergence (Barro and Sala-i Martin, 1991; Bernard and Jones, 1996; Rey and Montouri, 1999). However, some question if these long run trends are now being reversed (Ganong and Shoag, 2015). Moreover, both σ and β convergence have been subjected to much criticism in the regional science literature for their neglect of spatial dependence and spatial heterogeneity - characteristics of spatially referenced data that tend to be the norm rather than the exception. These forms of convergence also provide only summary views of the distribution of regional incomes and are generally silent on the internal dynamics of the distribution (Rey and Le Gallo, 2009). These criticisms have led to a related literature in spatial distribution dynamics where a new set of exploratory methods have been suggested to study the full distribution of regional incomes and the role of spatial effects in their evolution (Rey, 2014).

2.3 Interpersonal and Interregional Inequality - Separated at Birth?

While the literatures on social and regional inequality have matured since Alonso's paper, they have done so as largely separate endeavors with only limited cross fertilization. Indeed, as Metwally and Jensen (1973) note, measures of interregional inequality fail to take into account interpersonal income inequality either nationally, or within regions. By the same token, focusing on the aggregate national personal income distribution masks the geographical dimensions of inequality dynamics.

There are good reasons for considering personal and regional income inequality jointly. The work on interpersonal income inequality has used measures of inequality defined on personal income distributions for each state, and then focused on examining the determinants of these derived measures. By contrast, the interregional inequality literature has used an average income measure (typically per capita) for each region and explored the distribution of these averages over space and time.

Consequently, the two literatures are studying different moments of the same distribution. More specifically, let $y_{j,r,t}$ represent the income of individual j in region r in period t. The interpersonal inequality literature has focused on measures related to the dispersion in the distribution of $f(y_{i,r,t})$ within a particular region:

$$\sigma(y)^2_{r,t} = \frac{1}{N_{r,t}} \sum_{j \in r} (y_{j,r,t} - \bar{y}_{r,t})^2 \tag{1}$$

where $\bar{y}_{r,t} = \frac{1}{N_{r,t}} \sum_{j \in r} y_{j,r,t}$ and $N_{r,t}$ is the population of r in time t. Analysis of interpersonal inequality[5] has focused on the distribution of $\sigma(y)^2_{r,t}$ over $r = 1, 2, \ldots, R$ regions and $t = 1, 2, \ldots, T$ time periods, while the regional inequality has examined the distribution of $\bar{y}_{r,t}$ over the same regions and time periods.

In addition to the linkage between the distribution that ties the two literatures together, the second reason to consider both interpersonal and regional inequality dynamics is that there could be gains achieved from exploiting the complementary nature of the methodologies employed in the two literatures. In the interpersonal inequality literature, the focus has largely been on confirmatory modeling of the determinants of inequality or the relationship between inequality and growth. Conversely, in the regional inequality work, the emphasis has been on the underlying spatial patterns of the level of incomes and the dynamics of those patterns. As the latter is more exploratory in nature, while the former is confirmatory it seems prudent to adopt the exploratory approach to the case of interpersonal inequality. Essentially, the interpersonal inequality literature has simply skipped over the exploratory phase, and in this paper I revisit this issue.

A third justification for focusing on both regional interpersonal and interregional inequality is that together the two components represent a decomposition of total national interpersonal income inequality (Rietveld, 1991). This follows from the definition of the terms in (1), which can be extended to measure the total inequality (variation) in the national system:

$$\sigma(y)^2_t = \frac{1}{N_t} \sum_{j} (y_{j,t} - \bar{y}_t)^2 \tag{2}$$

where $\bar{y}_t$ is the national mean of incomes in period t. The variance of national personal incomes can then be decomposed into interregional and aggregate intraregional components:

$$\sigma(y)^2_t = \sigma(y)^2_{INTER,t} + \sigma(y)^2_{INTRA,t} \tag{3}$$

[5]The specific measure of inequality and dispersion varies across the different studies, the variance is used here to represent the general case.

with

$$\sigma(y)^2_{INTER,t} = \frac{1}{N}\sum_r N_r(\bar{y}_{r,t} - \bar{y}_t)^2 \tag{4}$$

and

$$\sigma(y)^2_{INTRA,t} = \frac{1}{N}\sum_r \sum_{j\in r}(y_{j,r,t} - \bar{y}_{r,t})^2. \tag{5}$$

The recent focus on inequality in the US has been concerned with (2). On the one hand, this has, to date, ignored the underlying components in (4) and (5). Alonso's two bells, on the other hand, do not consider the decomposition between interregional and intraregional inequality explicitly. Rather, his definition of interpersonal income inequality is (2), while by interregional inequality Alonso pointed to (4). Aggregate intraregional variance is ignored in his five bell system, but could be viewed as a derived decomposition:

$$\sigma(y)^2_{INTRA,t} = \sigma(y)^2_t - \sigma(y)^2_{INTER,t} \tag{6}$$

In what follows, I explicitly consider both interregional and aggregate intraregional variance together.

2.4 Bells in space

The bell analogy, while a powerful metaphor to help frame our thinking about inequality dynamics, also brings to the fore an important issue regarding distributions. More specifically, one is often naturally drawn to think of a bell as a stylized representation of a Gaussian distribution, and in the case of questions about income inequality distributions are a central concern. However, in the regional context, there are two problems with this tendency. The first is that the bell as distribution metaphor is different from what Alonso suggested as his view was that the bell traced out the path of a scalar summary measure of some distribution over time. For per capita income, that summary measure is the mean of the distribution for a set of regions, with the distribution being measured at each point in time. For personal income inequality the summary measure is something like a Gini coefficient and the bell traces its evolution over time, but again the statistic is derived from distributions of incomes measured at different points in time.

The second issue with the bell analogy is that the distributions under consideration are explicitly univariate distributions. Without this, the scalar summary measures of those distributions lose their conceptual underpinnings. This perspective comes at a cost however, as univariate distributions do not afford a consideration of spatial dependence or spatial heterogeneity. Spatial dependence becomes relevant whenever there is potential for the regions to interact, which would be reflected in migration, capital flows, trade and other phenomena that tie regions together.

Spatial heterogeneity would be reflected in situations where different subsets of the regions in the system display different types of behaviors, such as in the case of convergence clubs (Chatterji and Dewhurst, 1996) or poverty traps (Bowles et al., 2008), which may be driven by variations in economic structure (i.e., industry mix, demographic composition), across regional economies. The presence of either spatial dependence or spatial heterogeneity requires a shift in thinking from a univariate to a multivariate perspective since the latter affords the formal representation of these spatial effects.

Here we see another asymmetry in the two inequality literatures. The regional convergence literature has embraced the spatial dimensions in empirical, and to a lesser extent, theoretical, work. By contrast, the work on intraregional interpersonal income inequality has treated the observations from each of the regions as independent from those in other regions. The determinants of interpersonal income inequality within a state have been viewed as originating within that state - spatial interactions have been largely ignored. Given that there is growing evidence that the adoption of spatial methods, be they spatial econometrics or exploratory spatial data analysis, has provided important insights in the regional convergence literature, it seems worthwhile to extend these methods to the spatial dynamics of interpersonal regional income inequality as well.

3 Methods

The joint consideration of interpersonal regional income inequality and interregional income inequality requires the development of times series of observations on both types of inequality for each region within a national system. The two series are then analyzed via the same set of space-time analytics.

3.1 Data

The data used to measure state level interpersonal income inequality comes from a unique series constructed by Frank (2009). It is based on pretax adjusted gross income reported by the United States Internal Revenue Service which includes wages and salaries, capital income, and entrepreneurial income. The particular series examined in this paper are the income shares of the top percentile (S01) and top decile (S10) of the population annually for the period 1916-2012.

In addition to the income shares, data on per capita income for the states is obtained from the US Department of Commerce, Bureau of Economic Analysis[6] covering the period 1929-2012. State per capita incomes (SPI) are normalized relative to the national mean ($USPI$) for each year in the sample: $RSPI_{r,t} = \frac{SPI_{r,t}}{USPI_t}$.[7]

3.2 Methods: Distributional Dynamics

The central focus in this paper is an examination of the distributional dynamics of interpersonal and regional income inequality in the US over the period. More specifically, the internal distributional dynamics which reflect the extent of mobility of the states within the respective distributions over time are a key concern. Both the summary measures of mobility and the role of spatial structure and interactions are considered.

3.2.1 Discrete Markov Chains

The departure point for investigating inequality dynamics is the estimation of discrete Markov chains (DMC). These are formed for regional series at two points in time: $y \in [0, \infty)$ and $y_{t+d} \in [0, \infty)$ with cummulative distribution function $F(y_t, y_{t+d})$. The DMC maps $F(y_t, y_{t+d})$ into a $k \times k$ transition matrix, where k is the number of discrete space states the chain can be in at any moment in time. States of the chain are defined as: $0 \leq c_{1,t} \leq c_{2,t} \leq \ldots \leq c_{k,t}$. The transition probability matrix for the DMC takes the following form:

$$p_{i,j} = \frac{Pr(c_{i-1,t} < y_{r,t} \leq c_{i,t} \cap c_{j-1,t+d} < y_{r,t+d} \leq c_{j,t+d})}{Pr(c_{i-1,t} < y_{r,t} \leq c_{i,t})} \tag{7}$$

[6]US Bureau of Economic Analysis, "Annual state personal income and employment, all tables and areas", http://www.bea.gov/regional/downloadzip.cfm (accessed May 14, 2014).

[7]The results that follow are conditioned upon the choice of the state as the unit of analysis. This is driven by the availability of the long time series at this spatial scale. Finer spatial scales, such as counties, would limit the temporal frequency to decades. Sensitivity of the results to changes in spatial scale and temporal frequency remain for future research.

where $y_{r,t}$ is the observed value of the series for region r in period t. Thus, (7) gives the conditional probability that a region r in class i in period t moves into class j in period $t + d$.[8]

One assumption generally made in the literature is that these probabilities hold for all R regions and time periods. This allows for the estimation of P using paired samples of $(y_{r,t}, y_{r,t+d})$ $\forall r = 1, 2, \ldots, R$ drawn from $F(y_t, y_{t+d})$ using maximum likelihood:

$$\hat{p}_{i,j} = \frac{\sum_{r=1}^{R} I(c_{i-1,t} < y_{r,t} \leq c_{i,t} \cap c_{j-1,t+d} < y_{r,t+d} \leq c_{j,t+d})}{\sum_{r=1}^{R} I(c_{i-1,t} < y_{r,t} \leq c_{i,t})} \tag{8}$$

and

$$\hat{\pi}_{i,t} = \frac{1}{n} \sum_{r=1}^{R} I(c_{i-1,t} < y_{r,t} \leq c_{i,t}) \tag{9}$$

where $I(.)$ is an indicator function with value 1 if the condition is true and 0 otherwise, and $\hat{\pi}_{i,t}$ is the marginal probability of a region being in discrete state i of the distribution in time t.[9]

The discrete Markov chain framework can be used to examine a number of dimensions of regional inequality distribution dynamics. These include different measures of the mobility in the distribution reflecting specific types of movement within the distribution. Additionally, comparison of the dynamics across regional inequality series or at different points in time allows for an examination of alternative forms of heterogeneity in the dynamics.

The question of whether the series can be viewed as a single Markov chain, or M separate chains is addressed through a test of homogeneity of the Markov transition probability matrices. Following Bickenbach and Bode (2003) I adopt two formal tests of homogeneity:

$$Q^{(M)} = \sum_{m=1}^{M} \sum_{i=1}^{n} \sum_{j \in A_i} n_{i|m} \frac{(\hat{p}_{i,j|m} - \hat{p}_{i,j})^2}{\hat{p}_{i,j}} \tag{10}$$

$$H_o: \; p_{i,j|m} = p_{i,j} \; \forall m = 1, 2, \ldots, M$$

[8] I am re-purposing subscripts here to index discrete states of the chain, rather than individual regional economies.

[9] Space limitations prevent a more detailed treatment of the DMC and related methodological issues. For more details see Rey (2015).

$$Q^{(M)} \sim \chi^2 \left(\sum_{i=1}^{N} (a_i - 1)(b_i - 1) \right)$$

where a_i is the number of elements in A_i which is the set of nonzero transition probabilities in the ith row of the transition matrix estimated from the entire sample, and b_i is the number of the regimes for which a positive number of observations is available for the ith row ($B_i = \{m : n_{i|m} > 0\}$).

The Likelihood ratio test for the same null takes the following form:

$$LR^{(M)} = 2 \sum_{m=1}^{M} \sum_{i=1}^{n} \sum_{j \in A_{i|j}} n_{i,j|m} ln \frac{\hat{p}_{i,j|m}}{\hat{p}_{i,j}} \tag{11}$$

where $A_{i|m} = \{j : \hat{p}_{i,j|m} > 0\}$ is the set of nonzero transition probabilities in the ith row of the transition matrix estimated from the mth regime. $LR^{(M)}$ has the same asymptotic distribution as $Q^{(M)}$.

The homogeneity testing framework is quite general and permits the examination of a number of interesting special cases reflecting alternative definitions of the regimes. For example, if different variables can be used to measure inequality, a test of the similarity of the dynamics of the inequality reflected in the two series can be considered using this framework. In the current context, we can compare intraregional interpersonal inequality and its dynamics over space to that of interregional income inequality dynamics.

3.2.2 Spatial Autocorrelation

To complement the focus on distributional dynamics, a spatial perspective is also adopted to explore the nature and extent of any spatial clustering in the two inequality series. For each year and series, both global measures of spatial autocorrelation and local indicators of spatial association are calculated. The global measure is Moran's I:

$$I_t = \frac{n}{S_0} \frac{\sum_r \sum_s z_{r,t} w_{r,s} z_{s,t}}{\sum_r z_{r,t}^2} \tag{12}$$

where $w_{i,j}$ is the value from a row-standardized, queen-based contiguity matrix for the 48 conterminous US states, S_0 is the sum of all the elements in W, and $z_{r,t} = y_{r,t} - \bar{y}_t$. The global measure at time t can be used to test if the inequality series departs from a random spatial process.

The local indicators of spatial association are:

$$I_{r,t} = \frac{n}{S_0} \frac{\sum_s z_{r,t} w_{r,s} z_{s,t}}{\sum_r z_{r,t}^2} \tag{13}$$

which provide for an exploration of localized spatial clustering which might be driving the global pattern from (12) or departing from the global process (Anselin, 1995).

3.2.3 Space-Time Measures

To examine the role of space in shaping the distributional dynamics, a number of spatial extensions to the DMC are also employed. The spatial Markov chain (Rey, 2001) conditions the transition probabilities facing a regional series on its regional context. This is a specific form of the general homogeneity framework above, where the regimes are defined based on the spatial lag of the inequality series. More specifically, the spatial lag is defined as $L_{r,t} = \sum_s w_{r,s} y_{s,t}$ and is itself discretized into quintiles. A formal test of whether the transitional dynamics are homogeneous across the regimes based on the spatial lag quintiles is then carried out.

4 Results

4.1 Dynamics of Inequality

Figure 1 contains the time series for the mean income shares claimed by the richest 0.10 (S10) and 0.01 (S01) of individuals, with the means taken over the states. The two shares move in concert and reflect the general U-pattern reported by Piketty and Saez (2006) where high levels of inequality mark the beginning of the sample followed by a long period of declining inequality from the early peak in 1930 through to 1980. This decline sharply reversed in the 1980's returning levels of inequality to their historical highs.

[Figure 1 about here.]

Figure 2 reports the maximum of the income shares for S01 and S10. In the most extreme case, Florida's 0.10 income share reached almost 0.80 of total personal income in 1929, with its 0.01 share claiming an astounding 0.60 of total personal income for the state. While the maximum shares display the initial decline from the peaks that were seen in the average shares, the growth in the maximum shares after 1980 is not as pronounced as the increase in the mean inequality seen in Figure 1.

[Figure 2 about here.]

Figure 3 displays the evolution of the global quintile distribution over time.[10] The number of states with 0.01 income shares falling into each quintile fluctuates in interesting patterns. Generally speaking, three different epochs where the quintile distribution takes on different forms can be identified. In the early part of the sample up to 1940 the upper quintiles dominate reflecting a period of high personal income inequality. In the second epoch, 1940-80, the first and second quintiles grow in importance at the expense of the fifth quintile, which starting in 1966 up until 1988 contained no states. The final epoch starts in 1988 with the resurgence of the fifth quintile and its clear dominance. Indeed, for the years 2004-2008 all states have 0.01 shares in the fifth global quintile.

[Figure 3 about here.]

If the income share quintile distribution is compared to the global quintile distribution for relative per capita income of the states in Figure 4 clear distinctions between these two series emerge. For relative incomes, there is a general pattern of convergence as the first and fifth quintiles begin the sample period as dominant but loose states over time. The internal quintiles (Q2, Q3, Q4) gain states together throughout most of the period with a shift towards the end of the sample where the middle quintile begins to shrink, while the second and fourth continue to expand. There is also a renewal of growth for the first and fifth quintile towards the very end of the sample. Unlike the case for the income share quintile distribution, there are no clear epochs in the evolution of the per capita income quintile distribution. Moreover, the each of the five quintiles in the share distribution experiences periods where there are no states falling in that quintile, while for the per capita quintile distribution none of the global quintiles is ever empty.

[Figure 4 about here.]

4.2 Spatial Distribution of Inequality

Figure 5 displays the global quintile maps for the 0.01 share of incomes for the 48 lower US states in selected years. Since they are derived from a pooling of all annual series, the quintiles are fixed for each of the maps in order to more readily visualize the evolution of the spatial patterns. Examination

[10] Global quintiles which are defined for the pooled annual series: $Q(VEC(Y))$ where Y is an $R \times T$ matrix. Local quintiles are defined for each year, or column of Y: $Q(Y_{.,t})$.

of the global quintiles reveals that the maximum share of the top 0.01 of households was 0.608 over the sample period with a minimum of 0.062. To enter the fifth quintile required that the 0.01 share exceed 0.151 in a given year. The evolution of the map patterns reveals the spatial footprint of the summary inequality dynamics behind Figures 1-3.

While the general U pattern of interpersonal income inequality in the US has been much commented upon, the spatial distribution of inequality and the evolution of these patterns suggests that even when the overall level of inequality are roughly equal, as in the first and third epochs in the time series in Figure 1, the spatial distribution associated with these high-inequality periods can be distinct. In the modern high-inequality era the spatial homogenization of inequality is much stronger than in the earlier high inequality era of the 1920s. In the third epoch the increase in inequality was associated with a rapid change in its spatial distribution between 1988, where states are in either the first or second quintiles, and 1997 where all states move to the fourth or fifth quintiles. As was seen in the time series plots of the summary income shares, this period reflected rapid increase in inequality and this is clearly reflected in its spatial distribution, as by 2005 each state's 0.10 income share is in the upper quintile. By contrast, the spatial patterns of inequality in the 1920 period are much more heterogeneous.

The time series of maps for state relative per capita incomes by global quintile for the same select years are shown in Figure 6. In contrast to the maps of 0.01 income shares, the state per capita income maps display considerably less differentiation across the three epochs. The general trend is a reduction in dispersion in relative per capita incomes reflected in states moving out of the first and fifth quintiles over time, as was suggested by Figure 4. However, there is a clear spatial signature to these changes as the cluster of low income southeastern states in the early epoch breaks apart beginning with the second epoch.

The maps provide a rich depiction of the changing structure of personal and spatial income inequality in the US At the same time, this depiction is a challenge to summarize from a visual perspective. In order to address this challenge we can turn to a series of formal analytics to provide more specific insights into these complex dynamics.

[Figure 5 about here.]

[Figure 6 about here.]

4.3 Homogeneous Inequality Dynamics?

The first set of tests explore the question of whether the different regional series display distinct transitional dynamics over the study period.[11]

Beginning with the local quintile distributions, Table 1 reports the test of homogeneity in the Markov transition probability matrices between the 0.01 percentile and 0.10 percentile income shares. The test is based on the quintile distribution of the state inequality shares, as measured by the 0.01 share or the 0.10 share. The transition matrix under the null $P(H0)$ is estimated by pooling the two series as a single chain, while the bottom two tables report the marginal transition probability matrices estimated for each share series separately. Both the likelihood ratio and χ^2 tests are marginally significant ($p = 0.10$) and an examination of the diagonal elements of the two marginal tables reveals that the state 0.01 percentile distribution displays relatively greater mobility relative to the distribution based on the 0.10 shares. Given that the 0.01 and 0.10 share series are correlated by construction, in what follows I focus on only the 0.01 shares in comparisons with measures of regional inequality dynamics.

[Table 1 about here.]

The question of whether the dynamics of interpersonal and regional inequality are distinct is next examined in Table 2 where the estimated Markov transition matrices for the global quintile series for the S01 and relative per capita income series RSPI are tested for homogeneity. Both the likelihood ratio and Q tests of homogeneity are significant.[12] Moreover, the mobility in the S01 series is substantially greater than that in the per capita income series as reflected in the larger diagonal values in the table for the second series.

[Table 2 about here.]

4.4 Spatial Mobility Dynamics

4.4.1 Global and Local Spatial Autocorrelation

Figure 7 portrays the time series for the z-values of Moran's I global measure of spatial autocorrelation for the per capita income and one-percent income

[11] All computations are based on PySAL (Rey and Anselin, 2010).

[12] The same time period is used in comparing the dynamics of S01 and RSPI, 1929-2012, while in Table 1 the longer time series is used for S01 and S10, 1916-2012.

shares over the period. Relative to the critical value of 1.96 (dotted horizontal line), there are clear differences between the two series with regard to the presence of spatial dependence. For the per capita series, spatial dependence is found each year in the sample, displaying a drop from its strongest levels earlier in the series until 1980 at which point the dependence reaches its lowest level. However, even at this minimum the dependence is still significant and following 1980 there is an increase in the strength of spatial dependence. By contrast, the global measure for the one percent income share is never significant during the period 1929-2012. In other words, from a whole-map or global perspective, state interpersonal income inequality is randomly distributed in space.

[Figure 7 about here.]

Turning to the local measures, Figure 8 displays the time series of counts for the number of significant local statistics for each series. Now there is evidence of local clustering despite the finding of no global spatial autocorrelation for S01. At the same time, there is a greater extent of local clustering for RSPI than for S01, reflecting similar finding for the global case. For RSPI, the pattern for the evolution of the number of significant LISAs is roughly in-line with the pattern of the global measure.

[Figure 8 about here.]

Table 3 decomposes the total counts from Figure 8 by state and which quadrant of the Moran Scatter Plot the significant local statistic falls in. For the RSPI series, there are two dominant groups of states, those falling in the High-High (HH) quadrant in the majority of years (562 instances) including the northeastern states (CT, DE, MA, NJ, NY, PA, RI), and those comprising the Low-Low (LL) group (675 instances) which includes the southern states (AL, AR, FL, GA, LA, MS, NC, SC, TN, TX). Less common are the spatial outliers - local statistics falling into either the Low-High (LH) or High-Low (HL) quadrants.

The pattern for the decomposition of the LISA counts for the one percent shares is less defined than for the RSPI series. Only three states have at least 10 LISAs in the HH quadrant - reflecting spatial hot spots of interpersonal inequality, while only two states, FL and DE, fall in the LL quadrant in 10 or more years, in this case forming cold spots of income inequality. Moreover, the largest number of LISAs fall in the LH quadrant for the S01 series (140 instances), followed by the HL quadrant (70 instances). In other words, the S01 and RSPI series are distinguished by the former have more local outliers, while the latter having more clusters (hot and cold-spots).

[Table 3 about here.]

4.4.2 Spatial Markov

The results of the spatial Markov tests are reported in Tables 4 and 5 for the S01 and RSPI series, respectively. Recall that the test examines whether the transitional probabilities for the chain are influenced by the level of the spatial lag for the chain at the beginning of the transition period. For both series, the spatial independence assumption is rejected meaning that local context can shape the movement of the chain in the distribution. For example, on average states in the poorest quintile at the beginning of a period have an estimated probability of 0.924 of remaining in that quintile at the end of the year. However, when focusing on states in the first quintile surrounded by neighboring states also in the first quintile, that probability increases to 0.972 percent, while if the neighbors are in the fifth quintile the probability drops to 0.600 (Table 5).

For the income shares, on average, states with the highest levels of interpersonal inequality have a 0.858 probability of remaining in the fifth quintile if they began a year in that quintile. However, if a state in the fifth quintile of interpersonal income inequality is surrounded by states that are on average also in that quintile the probability increases to 0.875 (Table 4). In contrast to the cross-sectional setting where spatial dependence in the income shares was found to be weak or non-existent in most years, the dynamics of state personal income inequality are sensitive to spatial context as the assumption of one transition matrix applying across all observations is rejected.

[Table 4 about here.]

[Table 5 about here.]

5 Discussion and Conclusion

Using the US states over the period 1929-2012, this paper has examined two of Alonso's five bells with a particular focus on their space-time co-evolution. Application of exploratory space-time analytics reveals that the patterns of social, or interpersonal, and regional, or interregional, inequality are complex and display characteristics that were not considered in Alonso's original stylized model. Interpersonal inequality displayed a U-pattern resulting in levels of inequality at the end of the period actually exceeding the alarmingly high values found in the 1920's. By contrast, interregional income inequality between the US states has displayed a general decline up until the end of this period where convergence has slowed or even reversed.

In addition to the differences in the overall trends for the two types of inequality, their distributional dynamics are also found to be distinct with social inequality exhibiting greater mobility than interregional inequality, meaning that states move across the quintiles of the social inequality distribution more frequently than they do in the per capita income distribution.

The spatial patterns of these movements are also differentiated as per capita incomes are strongly spatially autocorrelated each year in the sample, while global spatial dependence is never found for social inequality. A local analysis, however, reveals evidence of pockets of hot and cold spots for interregional inequality, as well as spatial outliers for social inequality. Finally, spatial Markov tests reveal that the transitional dynamics for both series are not independent of the local context for a state economy as the estimated transition probability matrices for both social and interregional income inequality are found to be significantly different across regimes defined on the spatial lag of each series.

Alongside the distinct spatial patterns of interregional and interpersonal inequality are pronounced temporal differences in the spatial distribution of interpersonal inequality. The two periods of high interpersonal inequality, the 1920's and the post 1980 era, have substantially different spatial distributions with the latter distribution characterized by a spatial homogenization of high personal income inequality, while in the former period high interpersonal income inequality is more spatially concentrated along the northeastern and western states.

This homogenization of interpersonal income inequality has also coincided with a reversal of a long running trend towards regional income convergence. The causes of this reversal and its association with increasing interpersonal income inequality are poorly understood. Fan and Casetti (1994) argue that the Rustbelt-Sunbelt shift dominated the US economic landscape up until the late 1960s and was a major force in driving regional income convergence. Subsequently, sectoral shifts reflected in the loss of manufacturing jobs and their replacement with lower paying service resulted in a hollowing out of the personal income distribution. They suggest that the spatial impact of this restructuring may have been uneven with new service and financial sector growth being more prevalent in the traditional core.

In addition to deindustrialization, fiscal policies and political decentralization associated with the Reagan administration have been suggested as possible causes for increasing interregional inequality. Coughlin and Mandelbaum (1988) found that defense expenditures during the Reagan administration were spatially biased towards high income states and away from low income states, increasing interstate inequality.

The decentralization associated with Reagan's New Federalism gave individual states more freedom to shape economic development policies. Decentralization could have led to greater spatial inequalities through a variety of mechanisms such as lost economies of scale in addressing concentrated poverty and differences in institutional capacities and resources across regions, although the relationship between decentralization and spatial inequality may vary depending on the level of development of a nation (Rodríguez-Pose and Ezcurra, 2010).

At the same time, the trend towards spatially ubiquitous levels of high personal income inequality uncovered in the latter period of this study may suggest that policies at the national level, such as tax reforms (Stiglitz, 2014), and macroeconomic events, including the great recession, financial meltdown and housing market implosion, have had global effects resulting in greater inequality due to declining real incomes at the bottom and middle of the income distribution and the rise of private debt in the form of loans leveraging ephemeral house price increases (Essletzbichler, 2015; Galbraith, 2012).

Although the housing market bubble appeared to have global impacts in terms of increasing interpersonal income inequality, there is some evidence to suggest that it may have also slowed regional convergence. Ganong and Shoag (2015) argue that high housing costs in high income regions worked to dampen migration of low wage workers from poor to richer regions due to the price sensitivity of low income workers. This reduced the labor and human capital reallocation process that historically had been an engine of regional convergence in the US. In short, the returns to residing in productive regions net of housing costs have moved in opposite directions attracting skilled works but diverting in-migration of unskilled workers. The housing bubble and housing regulations are the argued causes of these house price changes.

The joint consideration of interpersonal inequality and interregional inequality reveals insights that could have implications for regional economic development polices. The greater mobility in interpersonal inequality, relative to average state incomes, suggests that polices may have more impact on reducing (or increasing) inequality within states than they do on relative state income growth. At the same time, the strong evidence of spatial dependence in the dynamics of both inequality series implies that states should not be considered independent actors as policies adopted by one state may have spillover impacts into neighboring states. Taking these policy spillovers into account would argue for a national or regional perspective on state economic development policies.

Application of exploratory space-time methods is a first step towards the call for the "simultaneous consideration" (Alonso, 1980, p 5) of interpersonal and interregional income inequality dynamics, and a more complete understanding of the dynamics of different types of inequality and their interdependencies. The empirical patterns uncovered here need to be considered from the lenses of existing regional inequality theory and personal income inequality theory with an eye towards their integration. Additionally, from a methodological point of view, the role of spatial context in the dynamics of both social and regional inequality need to be taken into account in future econometric work.

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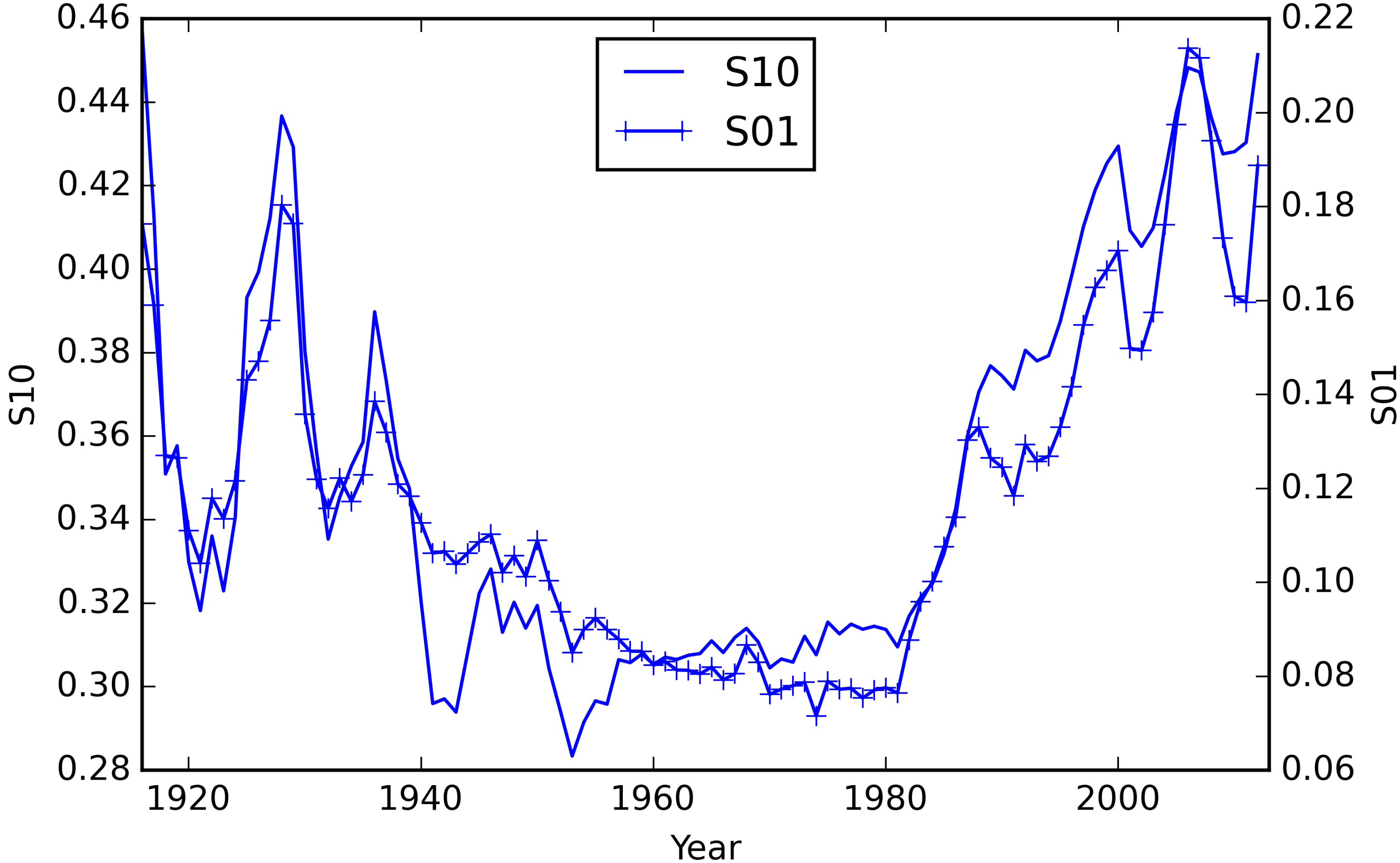

Figure 1: Mean 0.10 and 0.01 income shares for states, 1916-2012

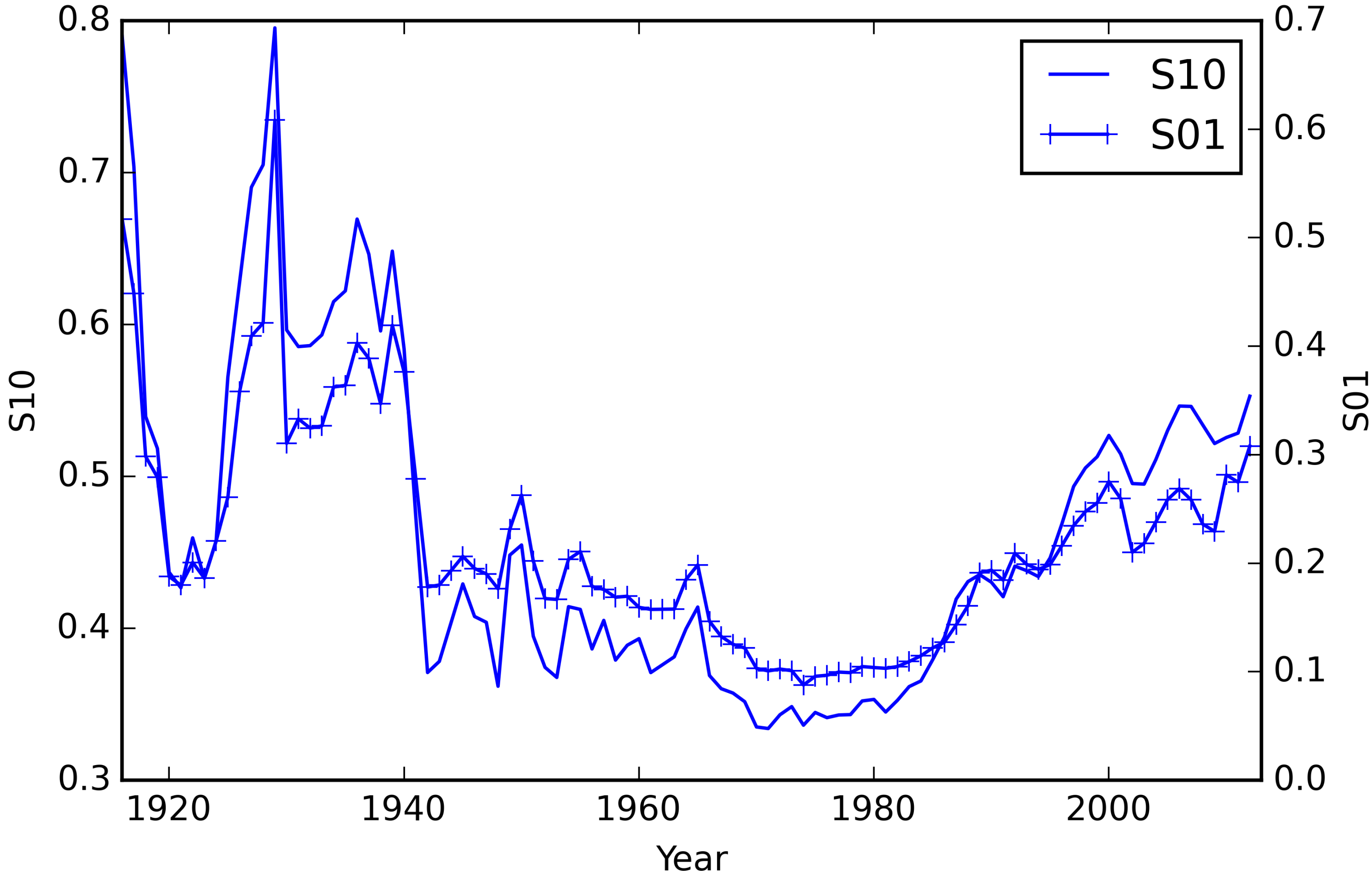

Figure 2: Maximum 0.10 and 0.01 income shares for states, 1916-2012

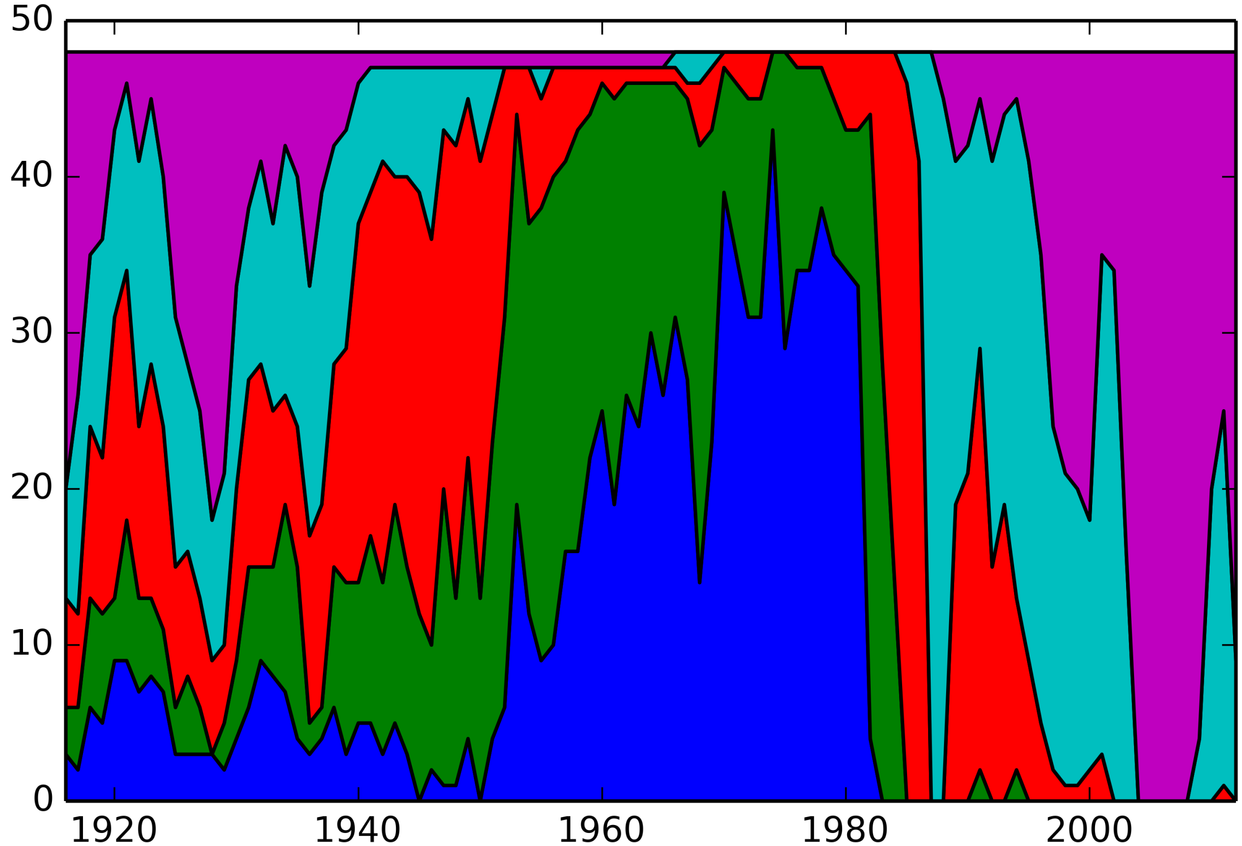

Figure 3: Global quintile distribution, 0.01 income shares for states, 1916-2012

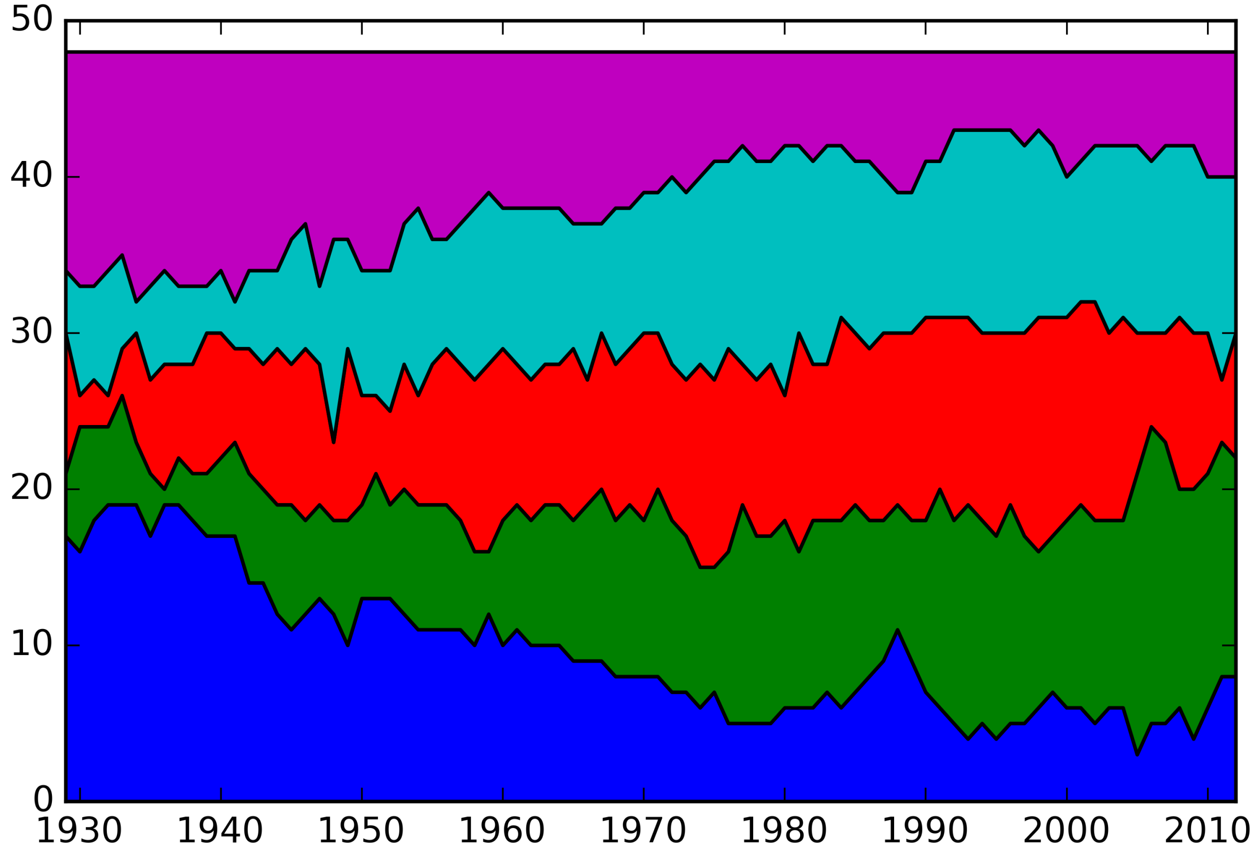

Figure 4: Global quintile distribution, per capita income for states, 1929-2012

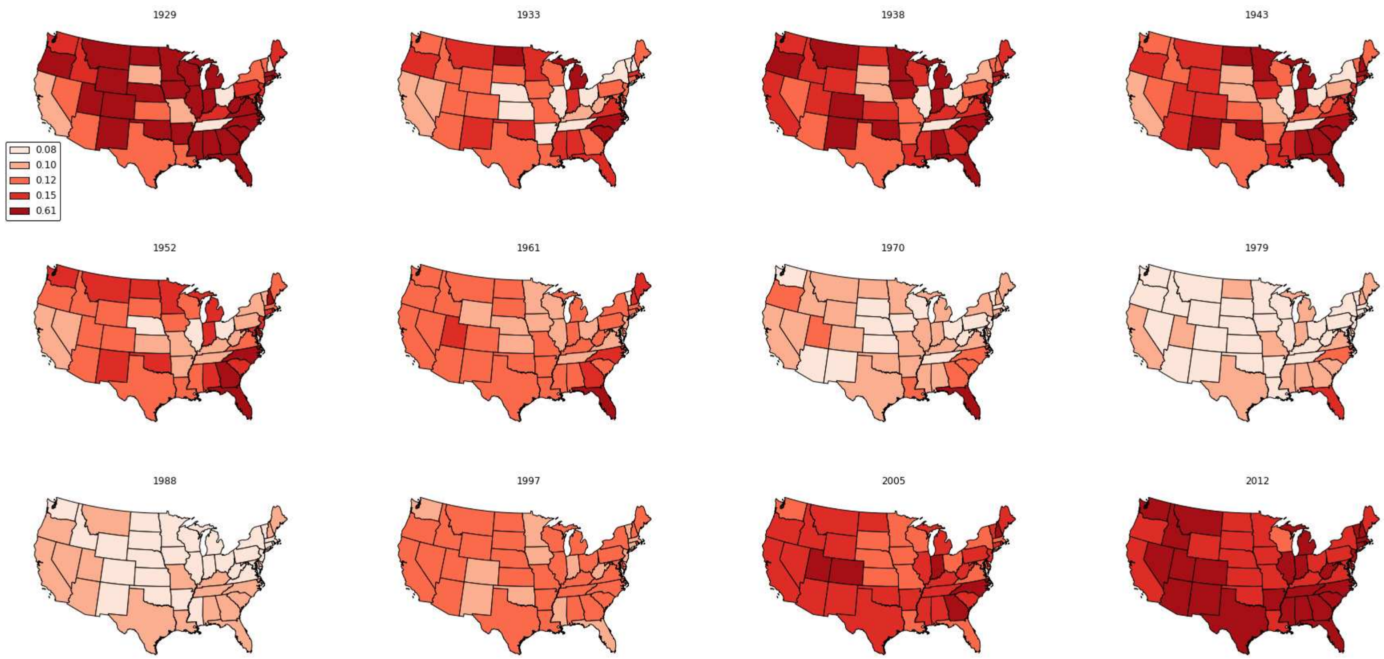

Figure 5: Top 0.01 income share by global quintiles selected years. Legend values are upper bound of each quintile.

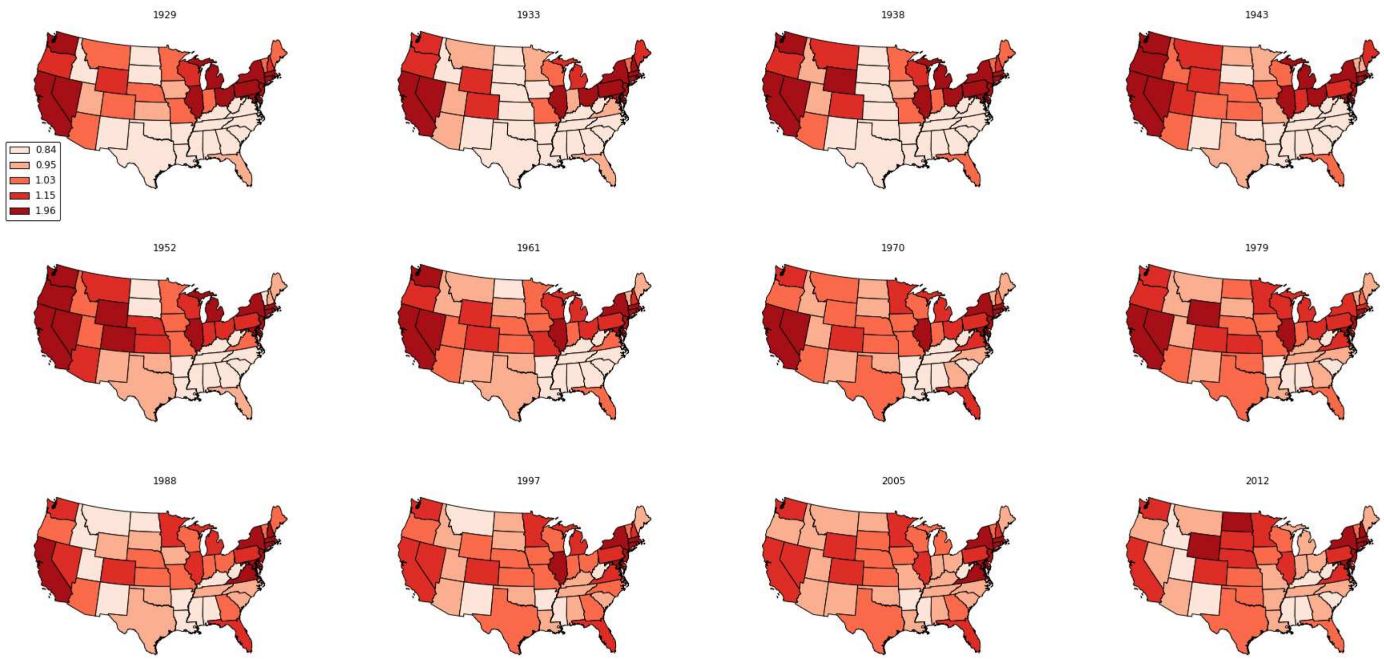

Figure 6: Relative per-capita incomes by global quintiles selected years. Legend values are upper bound of each quintile.

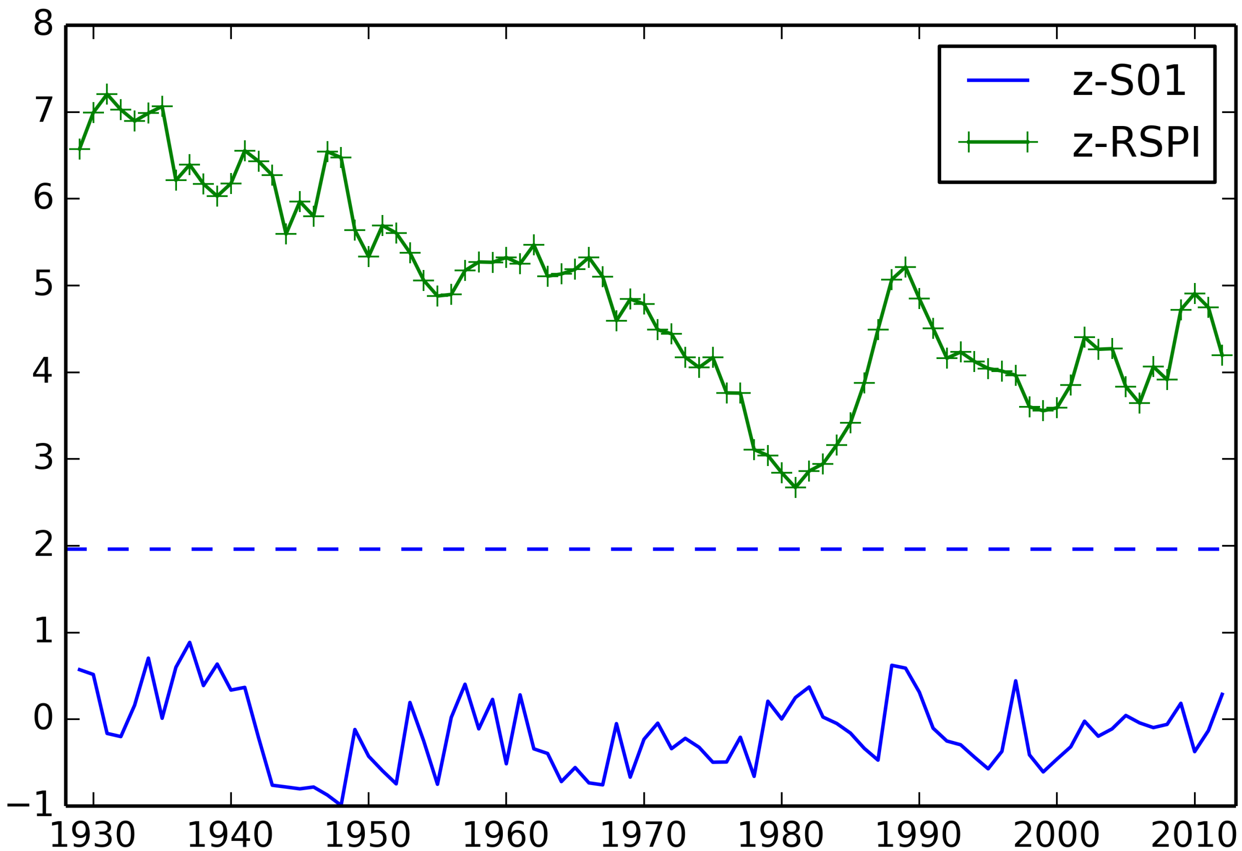

Figure 7: Global spatial autocorrelation, S01 and RSPI, z-values Moran's I, Queen Contiguity

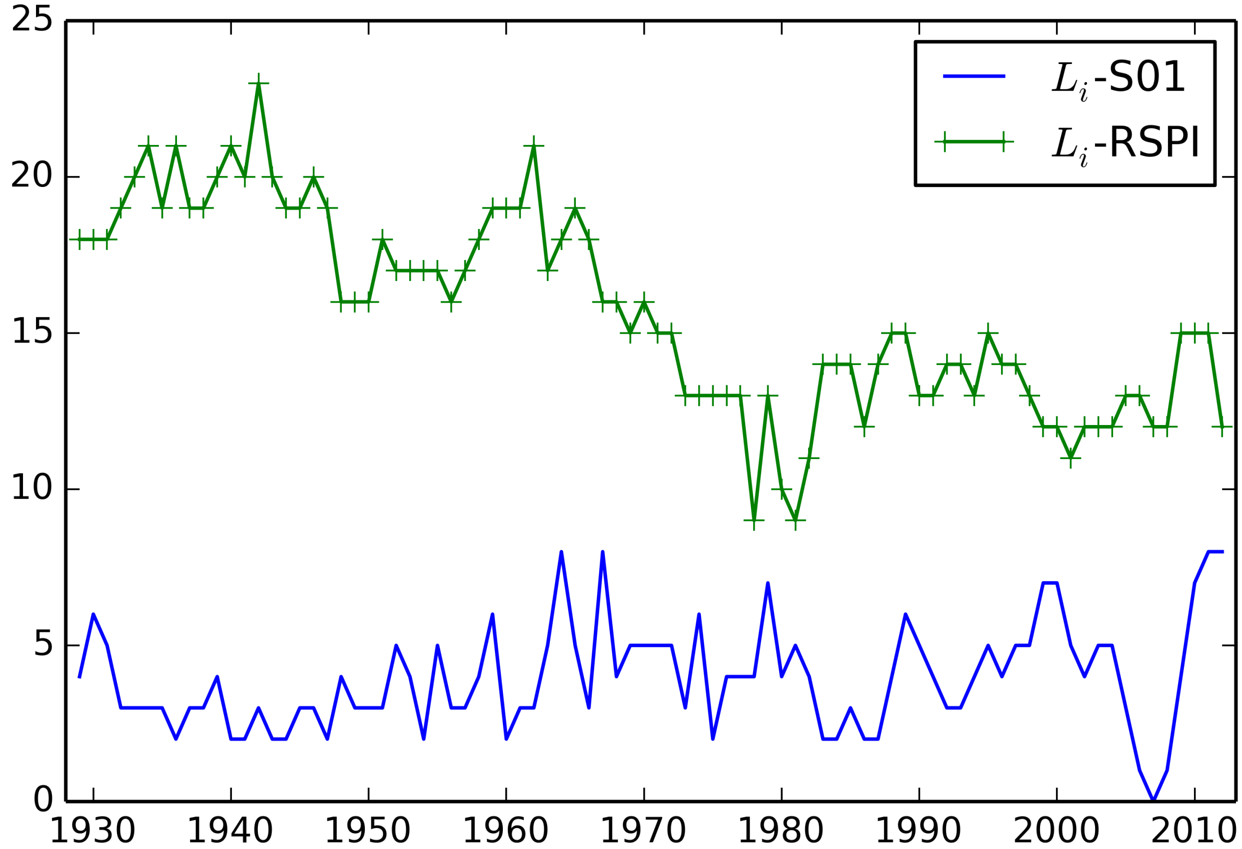

Figure 8: Local spatial autocorrelation, S01 and RSPI, number of significant Local Moran's I values, Queen Contiguity.

Markov Homogeneity Test					
Number of classes: 5					
Number of transitions: 9216					
Number of regimes: 2					
Regime names: S01, S10					
Test			LR		Q
Stat.			28.629		28.449
DOF			20		20
p-value			0.095		0.099
P(H0)	Q0	Q1	Q2	Q3	Q4
Q0	0.809	0.155	0.026	0.006	0.004
Q1	0.172	0.552	0.237	0.031	0.008
Q2	0.025	0.210	0.548	0.190	0.027
Q3	0.010	0.036	0.212	0.582	0.159
Q4	0.001	0.006	0.022	0.152	0.819
P(S01)	Q0	Q1	Q2	Q3	Q4
Q0	0.790	0.176	0.026	0.004	0.004
Q1	0.192	0.547	0.227	0.027	0.007
Q2	0.027	0.198	0.558	0.191	0.026
Q3	0.010	0.034	0.216	0.567	0.172
Q4	0.001	0.003	0.017	0.171	0.808
P(S10)	Q0	Q1	Q2	Q3	Q4
Q0	0.829	0.133	0.026	0.008	0.003
Q1	0.153	0.557	0.248	0.035	0.008
Q2	0.023	0.222	0.537	0.190	0.028
Q3	0.010	0.039	0.207	0.597	0.146
Q4	0.001	0.008	0.027	0.133	0.830

Table 1: Markov homogeneity tests, 0.01 percentile and 0.10 percentile shares, US state incomes

Markov Homogeneity Test					
Number of classes: 5					
Number of transitions: 7968					
Number of regimes: 2					
Regime names: GQS01, GQRSPI					
Test			LR		Q
Stat.			252.133		243.255
DOF			17		17
p-value			0.000		0.000
P(H0)	Q0	Q1	Q2	Q3	Q4
Q0	0.866	0.127	0.006	0.001	0.000
Q1	0.121	0.745	0.128	0.005	0.001
Q2	0.006	0.128	0.727	0.138	0.002
Q3	0.001	0.005	0.134	0.759	0.102
Q4	0.000	0.000	0.002	0.100	0.898
P(GQS01)	Q0	Q1	Q2	Q3	Q4
Q0	0.809	0.186	0.005	0.000	0.000
Q1	0.182	0.656	0.160	0.001	0.000
Q2	0.005	0.154	0.675	0.165	0.001
Q3	0.001	0.003	0.151	0.693	0.151
Q4	0.000	0.000	0.003	0.140	0.858
P(GQRSPI)	Q0	Q1	Q2	Q3	Q4
Q0	0.924	0.068	0.008	0.001	0.000
Q1	0.059	0.835	0.096	0.009	0.001
Q2	0.006	0.102	0.779	0.110	0.003
Q3	0.000	0.008	0.116	0.825	0.052
Q4	0.000	0.000	0.001	0.061	0.937

Table 2: Markov homogeneity tests, 0.01 percentile shares and per capita incomes, global quintiles, US state incomes

	RSPI					S01				
State	NS	HH	LH	LL	HL	NS	HH	LH	LL	HL
AL	24	0	0	60	0	84	0	0	0	0
AZ	76	3	5	0	0	78	0	0	6	0
AR	4	0	0	80	0	83	1	0	0	0
CA	75	9	0	0	0	84	0	0	0	0
CO	76	0	0	0	8	81	0	0	3	0
CT	16	68	0	0	0	64	1	19	0	0
DE	19	65	0	0	0	73	0	0	11	0
FL	48	0	0	31	5	63	0	0	13	8
GA	22	0	0	62	0	83	0	0	1	0
ID	69	3	12	0	0	79	0	0	0	5
IL	84	0	0	0	0	54	24	6	0	0
IN	84	0	0	0	0	76	0	0	1	7
IA	84	0	0	0	0	51	0	33	0	0
KS	84	0	0	0	0	75	0	0	1	8
KY	84	0	0	0	0	75	0	9	0	0
LA	1	0	0	83	0	84	0	0	0	0
ME	84	0	0	0	0	71	1	12	0	0
MD	84	0	0	0	0	71	0	0	3	10
MA	22	62	0	0	0	49	14	21	0	0
MI	84	0	0	0	0	43	5	36	0	0
MN	81	0	0	3	0	73	6	1	0	4
MS	0	0	0	84	0	80	0	0	0	4
MO	72	0	0	9	3	77	0	0	1	6
MT	78	0	0	6	0	84	0	0	0	0
NE	84	0	0	0	0	84	0	0	0	0
NV	82	1	0	1	0	84	0	0	0	0
NH	84	0	0	0	0	82	2	0	0	0
NJ	24	60	0	0	0	84	0	0	0	0
NM	84	0	0	0	0	84	0	0	0	0
NY	9	75	0	0	0	84	0	0	0	0
NC	45	0	0	39	0	83	0	0	1	0
ND	84	0	0	0	0	84	0	0	0	0
OH	76	0	0	8	0	82	0	0	1	1
OK	80	0	0	4	0	84	0	0	0	0
OR	39	45	0	0	0	84	0	0	0	0
PA	10	74	0	0	0	80	0	0	4	0
RI	4	77	3	0	0	84	0	0	0	0
SC	60	0	0	24	0	79	0	0	5	0
SD	82	2	0	0	0	84	0	0	0	0
TN	0	0	0	84	0	84	0	0	0	0
TX	6	0	0	73	5	69	0	3	0	12
UT	84	0	0	0	0	83	0	0	1	0
VT	33	17	34	0	0	70	14	0	0	0
VA	57	0	0	22	5	82	0	0	0	2
WA	84	0	0	0	0	84	0	0	0	0
WV	84	0	0	0	0	83	0	0	1	0
WI	83	1	0	0	0	84	0	0	0	0
WY	82	0	0	2	0	81	0	0	0	3
Total	2715	562	54	675	26	3701	68	140	53	70

Table 3: Local Autocorrelation Statistics by Moran Scatter Plot Quadrant, S01 and RSPI. NS: Not significant; HH: High (own), High (neighbor); LH: Low (own), High (neighbor); LL: Low (own), Low (neighbor); HL: High (own), Low (neighbor).

Spatial Markov Test S01					
Number of classes: 5					
Number of transitions: 3984					
Number of regimes: 5					
Regime names: LAG0, LAG1, LAG2, LAG3, LAG4					
Test			LR		Q
Stat.			194.130		339.776
DOF			60		60
p-value			0.000		0.000
P(H0)	C0	C1	C2	C3	C4
C0	0.809	0.186	0.005	0.000	0.000
C1	0.182	0.656	0.160	0.001	0.000
C2	0.005	0.154	0.675	0.165	0.001
C3	0.001	0.003	0.151	0.693	0.151
C4	0.000	0.000	0.003	0.140	0.858
P(LAG0)	C0	C1	C2	C3	C4
C0	0.816	0.179	0.004	0.000	0.000
C1	0.211	0.729	0.061	0.000	0.000
C2	0.000	0.262	0.714	0.024	0.000
C3	0.167	0.000	0.167	0.500	0.167
C4	0.000	0.000	0.000	0.200	0.800
P(LAG1)	C0	C1	C2	C3	C4
C0	0.833	0.162	0.004	0.000	0.000
C1	0.178	0.639	0.184	0.000	0.000
C2	0.016	0.207	0.717	0.060	0.000
C3	0.000	0.020	0.255	0.667	0.059
C4	0.000	0.000	0.000	0.136	0.864
P(LAG2)	C0	C1	C2	C3	C4
C0	0.646	0.354	0.000	0.000	0.000
C1	0.126	0.615	0.259	0.000	0.000
C2	0.000	0.125	0.667	0.208	0.000
C3	0.000	0.000	0.215	0.718	0.068
C4	0.000	0.000	0.000	0.304	0.696
P(LAG3)	C0	C1	C2	C3	C4
C0	0.857	0.114	0.029	0.000	0.000
C1	0.204	0.537	0.241	0.019	0.000
C2	0.006	0.110	0.686	0.198	0.000
C3	0.000	0.000	0.139	0.711	0.150
C4	0.000	0.000	0.000	0.153	0.847
P(LAG4)	C0	C1	C2	C3	C4
C0	0.800	0.200	0.000	0.000	0.000
C1	0.250	0.375	0.375	0.000	0.000
C2	0.000	0.273	0.424	0.273	0.030
C3	0.000	0.005	0.087	0.647	0.261
C4	0.000	0.000	0.004	0.121	0.875

Table 4: Spatial Markov Test, S01, k=5

Spatial Markov Test RSPI					
Number of classes: 5					
Number of transitions: 3984					
Number of regimes: 5					
Regime names: LAG0, LAG1, LAG2, LAG3, LAG4					
Test			LR		Q
Stat.			173.190		195.109
DOF			64		64
p-value			0.000		0.000
P(H0)	C0	C1	C2	C3	C4
C0	0.924	0.068	0.008	0.001	0.000
C1	0.059	0.835	0.096	0.009	0.001
C2	0.006	0.102	0.779	0.110	0.003
C3	0.000	0.008	0.116	0.825	0.052
C4	0.000	0.000	0.001	0.061	0.937
P(LAG0)	C0	C1	C2	C3	C4
C0	0.972	0.026	0.002	0.000	0.000
C1	0.051	0.803	0.139	0.007	0.000
C2	0.009	0.151	0.717	0.123	0.000
C3	0.000	0.024	0.262	0.619	0.095
C4	0.000	0.000	0.000	0.286	0.714
P(LAG1)	C0	C1	C2	C3	C4
C0	0.777	0.182	0.033	0.008	0.000
C1	0.074	0.860	0.062	0.004	0.000
C2	0.000	0.103	0.806	0.091	0.000
C3	0.000	0.000	0.072	0.892	0.036
C4	0.000	0.000	0.000	0.195	0.805
P(LAG2)	C0	C1	C2	C3	C4
C0	0.844	0.156	0.000	0.000	0.000
C1	0.063	0.844	0.076	0.013	0.004
C2	0.016	0.089	0.801	0.089	0.005
C3	0.000	0.006	0.091	0.835	0.068
C4	0.000	0.000	0.000	0.132	0.868
P(LAG3)	C0	C1	C2	C3	C4
C0	0.948	0.039	0.013	0.000	0.000
C1	0.045	0.836	0.109	0.009	0.000
C2	0.000	0.073	0.794	0.129	0.004
C3	0.000	0.018	0.189	0.732	0.061
C4	0.000	0.000	0.005	0.071	0.924
P(LAG4)	C0	C1	C2	C3	C4
C0	0.600	0.400	0.000	0.000	0.000
C1	0.030	0.773	0.182	0.015	0.000
C2	0.010	0.136	0.728	0.126	0.000
C3	0.000	0.005	0.094	0.865	0.036
C4	0.000	0.000	0.000	0.023	0.977

Table 5: Spatial Markov Test, RSPI, k=5