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Scales of regional income disparities in the USA, 1955–2003

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Abstract

This article examines multiple dimensions of regional per capita income disparities in the USA between 1955 and 2003 with a particular focus on scalar effects. It combines various exploratory analytical tools of spatial disparities, including inequality indices, mobility indices, kernel density estimation, spatial autocorrelation statistics and scale variances, to analyse regional average per capita income distributions at multiple spatial scales, ranging from counties to multi-state regions. The analysis reveals previously unrecognised systematic patterns of cross-scalar dynamics, whereby spatial income disparities are increasingly more pronounced at smaller scales in the last few decades.

Keywords: ESDA (exploratory spatial data analysis), spatial income disparities, scalar effects, USA
JEL classifications: C21, O18, O51, R11, R12
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1. Introduction

This article examines multiple dimensions of regional per capita income disparities in the USA in the post-war period with a particular focus on scalar effects. Increasing socioeconomic disparities have been a growing concern in many industrialised countries in the past decades. In the USA, income inequality among individuals and households has been on the rise since the 1970s (Piketty and Saez, 2003; U.S. Census Bureau, 2006), and the widening income inequality has been attributed to various factors such as global trade-based integration, skill-biased technological changes and market-oriented institutional reforms. Some fear that these factors may also result in increased regional economic disparities within countries, typified by the increased dominance of the 'world cities' and selected high-tech cities, undermining smaller cities and rural towns.

Growing literature on regional income convergence in part reflects this emerging concern over regional economic disparities. This literature draws on various schools of economic theory, including neoclassical and endogenous theories, which share a focus on supply-side factors, and neo-Keynesian and Kaldorian theories that seek explanations of regional dynamics in demand-side factors. These theories typically concern β-convergence (for a comprehensive review, see Temple, 1999; Islam, 2003; Rey and Janikas, 2005) because one can derive empirically testable models of

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Table 1. Dimensions of spatial disparities

Dimensions	Tendencies	Measurements
Inequality	σ-Convergence σ-Divergence	Inequality index
Modality	Unimodality Multimodality (polarization or stratification)	Kernel density function (curve and surface)
Churning/mobility	Stabilization (inert) Destabilization (shuffling)	Probability transition matrix Mobility index (class and rank)
Clustering	Consolidation Fragmentation	Spatial autocorrelation statistic

convergence from the theories (hence this approach is considered 'confirmatory'). Essentially, β-convergence concerns the speed of differential growth rates in regional economic variables, such as regional per capita income, between two points in time (i.e. whether and how fast poor economies grow faster than rich economies). Nevertheless, the β-convergence approach embodies some theoretical problems such as unquestioned use of Cobb–Douglas production functions (Harcourt, 1972; Temple, 1999), parametric assumptions (Quah, 1996b) and the presumption of identical underlying convergence-generating processes (Martin and Sunley, 1998).

The confirmatory approach has been criticised also for its narrow empirical focus on spatial disparities, which makes it difficult to reveal and theorise historically and geographically complex evolutions of regional economies. 'Exploratory' approaches shed light on broader aspects of regional disparities that are not formalised within the mainstream economic theoretical frameworks (Ioannides and Overman, 2004; Rey and Janikas, 2005). For example, it is clear that regional convergence has not been a simple monotonic process historically (Martin and Sunley, 1998). Testing the presence of β-convergence overlooks such changes in pace and direction of convergence between two points in time. In this case, it is crucial to check for the trajectories of σ-convergence, which identifies interregional income inequality over time. The presence of σ-convergence has been traditionally identified with a successive decrease in inequality indices, such as Gini and Theil indices, while more recent methods include the unit root tests of time-series data (Bernard and Durlauf, 1996; Drennan et al., 2004).

In this article, I define spatial income disparities not solely as the matter of β- or σ-convergence, but as a multi-faced concept whose dimensions also include modality, churning and spatial clustering (Table 1). First, some observers of industrial restructuring since the early 1970s have argued that we have entered a period of the 'great U-turn', where economic inequality between social groups, and between regions, has begun to rise again after reaching the right end of the Kuznets–Williamson inverted U-curve[1] (Alonso, 1980; Harrison and Bluestone, 1988; Yazawa, 1999). This U-turn supposedly accompanies the polarisation of social and spatial income

1 Williamson's main finding (1965) is an empirical regularity where regional inequality first increases in early industrialization stage of a country, and decreases as the national economy reaches more mature stages of industrial development. This work is an extension of Simon Kuznets' hypothesis that *social* inequality first increases and then decreases as a country goes through sequential development stages.

distribution (i.e. a declining middle class), rather than a smooth dispersion across all income groups. Non-parametric methods, such as Markov transition matrices and kernel density surfaces, permit direct observation of the shapes of cross-sectional distributions (i.e. *modality*), which may have non-standard distributions (Quah, 1993, 1996b, 1997; Durlauf and Quah, 1999; Magrini, 2003). These tools have been used in recent analyses of regional income disparities in the USA (Johnson, 2000; Rey, 2001; Bickenbach and Bode, 2003), Brazil (Mossi et al., 2003), Europe (Quah, 1996a; Tortosa-Ausina et al., 2005) and Japan (Kang, 2004).

Second, another dimension of regional economic disparities is *churning* or *mobility* among regional economies. Some view that contemporary economy is characterised by increased regional economic instability or volatility due to accelerated commodity and capital flows, labour turnover, technological shifts and changes in consumption patterns. Empirical tools such as the Shorrocks index that captures the mobility of regional income levels (Hammond and Thompson, 2002), and the Tau statistics that captures the degree of rank stability (Rey, 2004b), can address this hypothesised trend by revealing distributional dynamics of regional incomes.

Third, yet another important dimension of regional economic disparities is *spatial clustering* of regional income levels—whether high-income regions are increasingly consolidating or fragmenting in space. Theoretical accounts such as endogenous growth theory recognise the role of spatial externalities that are affected by type and degree of technology spillovers, capital and labour migration, and commodity and information flows (Nijkamp and Poot, 1998). Arguably, such externalities may be becoming more important due to recent spatial economic integration that may result in an increased spatial autocorrelation of regional income levels (at some scale). The presence of such spatial dependence can invalidate the inferential basis of econometric methods because it violates the assumption of observational independence (Rey and Montouri, 1999; Rey and Janikas, 2005).

An increasing number of empirical studies in the convergence literature have begun to explore multi-faced dimensions of regional income disparities, but few empirical studies have dealt with the issue of spatial scales extensively.[2] In the geographic economic literature, there has been a tendency to assume that similar rules apply at all spatial scales, thus 'the same model is often used to explain spatial agglomeration and specialisation at vastly different scales, from the international level, to broad core-periphery patterns within nations, to local urban industrial concentrations, and even intra-urban neighbourhoods' (Martin, 1999, p. 78). Overman (2004) echoes this observation, saying 'in the hunt for general rules or tendencies, it is important to remember that what is true at a given spatial scale might not be true at another' (p. 513). On the other hand, recent geographic studies view that economic processes are not independent of scales at which subjects are observed and analysed (Sheppard and McMaster, 2004). The emerging body of scalar literature on globalisation, for example, identifies a critical shift in scales at which economic relations have been organised and governed from the early 1970s (Smith and Dennis, 1987; Smith, 1992; Jessop, 1994; Collinge, 1999; Brenner, 2001; Bunnell and Coe, 2001). This scalar shift is far more complex than the emerging

2 The term 'scale' carries two different meanings, and can be distinguished as 'resolution scale,' the smallest regional unit of analysis and 'study area scale,' the largest areal extent of analysis (cf. Sheppard and McMaster, 2004). This article uses the term 'scale' in the first sense without a qualifier.

dominance of the global scale, replacing the nation state scale (Sheppard, 2002), as transnational corporations still rely heavily on national policies and regulations (Dicken, 2003), while at the same time urban regions are arguably the new units of global competition (Scott, 1988, 1998; Storper, 1992, 1997; Porter, 1998).

Despite the rising awareness over the importance of scales in economic geography, there has been 'little or no discussion of whether there is an appropriate regional scale at which to analyse convergence, nor analyses that seek to determine whether different trends in regional convergence may be occurring at different spatial scales' (Martin, 1999, p. 78). Studies that use inequality decomposition techniques do touch on this issue by distinguishing sources of regional inequality within and between regional units (Nissan and Carter, 1993; Martin, 2001; Rey, 2004a; Shorrocks and Wan, 2005), but these studies typically do not conduct multi-scale analysis for three or more scales. It is also conceivable that the sources of income inequality are increasingly found at smaller spatial scales, possibly all the way down to the individual or household scales (in which case geographic space no longer matters in defining inequality). Few existing studies, however, have investigated whether and how far such a 'downscaling' of income inequality might have occurred. Finally, there has been virtually no research that examines the changes in modality and churning of regional income levels across multiple scales.

In what follows, I seek to gain a better understanding of the historical evolution of regional income distribution by analysing multiple dimensions of regional economic disparities at different spatial scales.[3] The research strategy adopted here is not to fit the reality to simple, highly generalised theories, but to simplify the complex reality to draw some general implications (cf. Ioannides and Overman, 2004). This study makes three major contributions to the regional convergence and inequality literature. First, unlike many previous studies that examine various types of regional income disparities in isolation, I synthetically analyse the multi-dimensional disparities by combining exploratory tools to characterise the nature of regional economic change in the period of restructuring and global economic integration. Such an analysis responds to and extends the call by Rey and Janikas (2005), who assert the need to understand the potential relationship between inequality and spatial dependence. Second, an explicit focus on scalar effects reveals previously unrecognised systematic patterns of cross-scalar dynamics in regional income disparities in the USA in the last several decades. In particular, the scale variance analysis that has been rarely used in the convergence literature, proves to be a useful technique to examine scalar effects. Third, this study makes an empirical contribution by distinguishing qualitative differences in the two episodes of temporary regional income divergence in the 1980s and the 1990s in the USA, which have not received sufficient attention in existing studies.

2. Revisiting state-scale analysis

2.1. Observations of trends

In the existing studies of σ-convergence or spatial income inequality in the USA, the state-scale has been the most common scale of analysis. Most of these studies show

3 Portions of the analysis in this study are conducted using *Space-Time Analysis of Regional Systems* (*STARS*), an open-source application for geospatial computation (http://regal.sdsu.edu/index.php/Main/STARS).

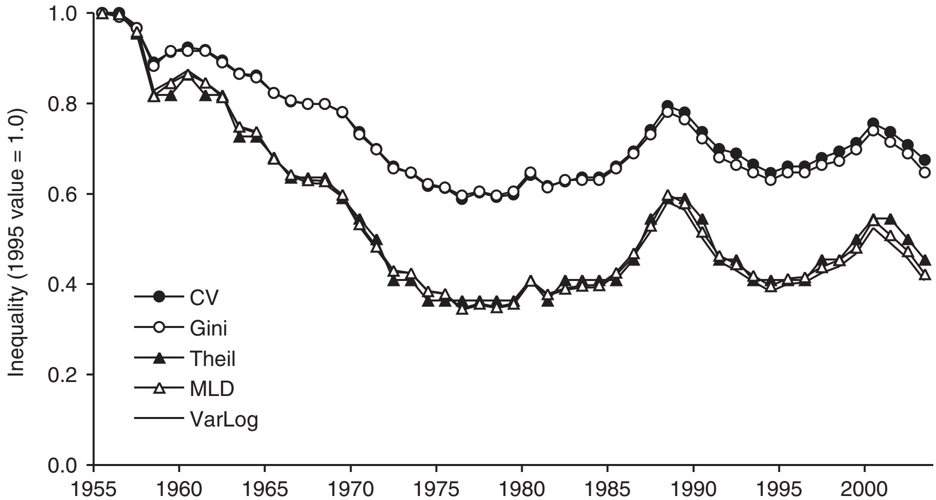

Figure 1. State per capita income inequality by CV, Gini coefficient, Theil index, MLD and VarLog, 1955–2003. To see relative differences among the indices, each index is normalized to its 1955 value.

a rapid convergence between the early 1930s to the mid-1940s, followed by a more moderate, but steady, convergence between the mid-1940s to the mid-1970s (Coughlin and Mandelbaum, 1988; Barro and Sala-i-Martin, 1995; Sherwood-Call, 1996; Rey and Montouri, 1999; Bernat, 2001; Rey, 2001). In the 1980s, some studies observed that the steady convergence may have halted and reversed into divergence starting in the late 1970s (Fan and Casetti, 1994; Coughlin and Mandelbaum, 1988). Nevertheless, the apparent divergence was rather short-lived, which calls the 'great U-turn' argument that focuses on structural changes and their long-term impact on spatial (as well as social) inequality in question.

Figure 1 shows state per capita income inequality for the contiguous 48 states between 1955 and 2003, essentially replicating the results of the earlier studies. To ensure that the results are not affected by the choice of inequality indices, I plot inequality trends for five major inequality indices: the coefficient of variation (CV), Gini index (Gini), Theil index (Theil), the mean logarithm deviation (MLD) and the variance of logarithm (VarLog).[4] Each series is normalised to its 1955 value (i.e. 1955 value = 1) to enable comparison among inequality indices, and to see relative changes in the indices over time.

The inequality trends show convergence from 1955 until the mid-1970s, but with little sign of further convergence after that. Instead, the post-1970s regional inequality trends are punctuated by two temporary divergence episodes peaking in the late 1980s and in the late 1990s as found in other studies (Barro and Sala-i-Martin, 1995; Rey and Montouri, 1999). In both divergence episodes, the three highest-income states were

4 Technical details of these five indices are explained in detail, and applied to international income inequality analysis in Firebaugh (2003). The only minor difference is that Firebaugh uses squared coefficient of variation (CV^2), rather than coefficient of variation (CV). See Cowell (1977) for more elaborated discussion of inequality indices, in general.

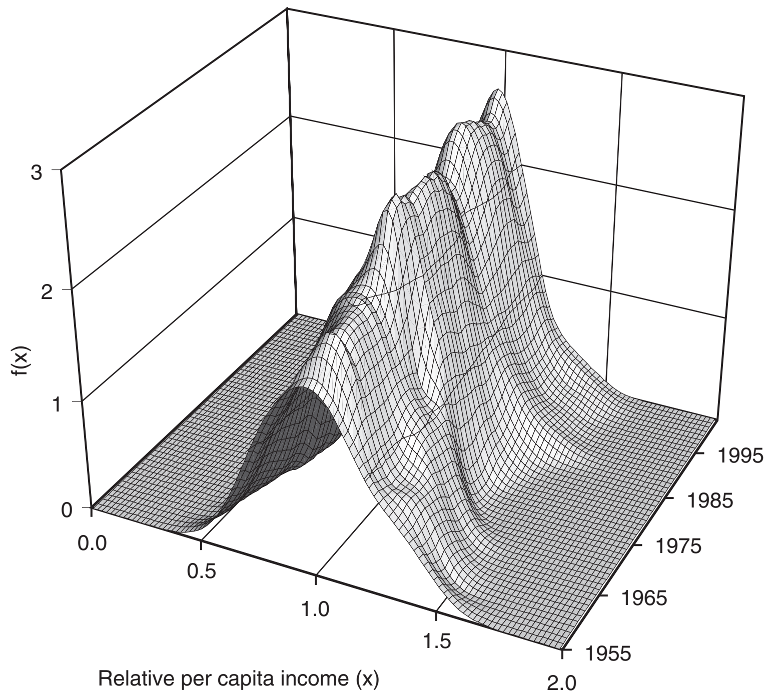

Figure 2. Distributional evolution of state per capita income, 1955–2003. Horizontal axis shows relative per capita income (state per capita income divided by the mean of all state per capita incomes) for a given year, and the vertical axis shows its probability density.

Connecticut, Massachusetts and New Jersey, while West Virginia and Mississippi were the lowest-income states. Despite the differences in actual values, the five indices can be basically divided into two groups based on the revealed patterns of convergence: CV and Gini as the first group, and Theil, MLD and VarLog as the second. Regardless, even these two groups show the same timings of peaks and troughs, suggesting that the choice of indices does not critically affect the temporal patterns.

Exploratory tools of regional income disparities provide further insights into US state-scale income disparities. First, in terms of modality, Figure 2 shows changes in the shapes of probability density curves for state income between 1955 and 2003. Unlike previous empirical studies that present probability density curves for selected years (Rey, 2001), Figure 2 illustrates income distributions as a continuous surface on an annual basis instead of only for selected years, allowing the visual inspection of temporal changes in distributions. To reduce year-to-year fluctuations, three-year averages of probability density are shown. The density curves appear to approximate normal distributions. Rising peaks around the mean income (1.0) until the mid-1970s indicate convergence of regional income levels. We observe two periods of temporary divergence in the late 1980s and 1990s as indicated by the lower peaks. The upper tails of the curves become longer from the late 1970s, skewing the curve positively, confirming the observation in Rey (2001), which indicates the income growth of a few rich states. It is clear, nonetheless, that the US state-scale analysis shows little evidence of polarisation or stratification of regional income distribution, a major concern for international income disparities (Quah, 1997).

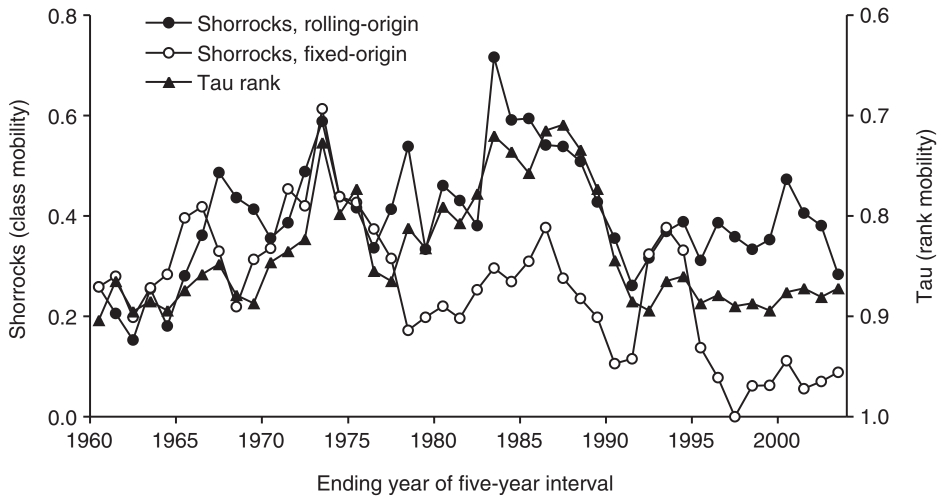

Figure 3. Mobilities of state income in Shorrocks (class mobility) and Tau (rank mobility) indices, 1955–2003, at five-year intervals.

Second, trajectories of distributional churning between 1955 and 2003 are shown in Figure 3. The Shorrocks indices show how a region's income level shifts from one class to another during a given time interval, where the classes can be defined based, for example, on quartiles or quintiles of income distribution (Shorrocks, 1978; Rey, 2001; Hammond and Thompson, 2002). I calculate Shorrocks indices using two methods. The first, 'rolling-origin' method uses quintiles based on the distribution at the beginning of each interval. The second, 'fixed-origin' method uses quintiles based on the initial period's distribution alone. For example, in the rolling-origin Shorrocks index, the 1975 distribution is used for the income classes for the 1975–1980 period, the 1976 distribution for the 1976–1986 period, and so on, whereas in the fixed-origin Shorrocks index, the five income classes are created based on the income distribution in 1955 for all periods. The figure shows both Shorrocks indices, representing the degrees of state income movements from one class to another in a five-year interval.

The time trend based on the rolling-origin method shows a generally increasing mobility from the mid-1960s to the mid-1970s, and a particularly high mobility in the 1980s, confirming the findings of Hammond and Thompson (2002). The high mobility in the recent decades may be considered 'deceptive' because this method will produce a high mobility index over time, if the overall distribution progressively converges (i.e. absolute degree of inter-class movements may be decreasing over time). The time trend based on the fixed-origin method shows that the most pronounced mobility index is observed in the 1970s, followed by more moderate levels in the 1980s and the 1990s. Both trends illustrate that the most recent decade cannot be characterised as a period of increased churning of state economies.

Increased churning across income classes need not imply changes in the relative positions (i.e. rankings) of state economies in the distribution (Rey, 2004b). Thus, Kendall's τ-statistic is also shown to give an insight into positional flux among regional economies (Figure 3). The time trend of income rank mobility resembles that of income class mobility (a low τ indicates high rank mobility). The early 1970s and the 1980s show the highest rank mobility index, followed by low mobility in the 1990s.

In particular, the rank mobility trend is similar to the income class mobility based on the rolling-origin quintiles. The correlation coefficient between the rank mobility and class mobility based on the rolling-origin quintiles is 0.782.[5] Hammond and Thompson (2002) argue that over a long period of time (1929–1999), state income distribution has shown substantial income class mobility, while rank association is largely preserved. Nevertheless, ranking changes do tend to occur during the period of high-income class mobility, and little evidence shows steady increase in either class or rank mobility in the post-1970s period as some globalization researchers may expect. In particular, the 1990s shows some of the lowest degrees of churning during the study period.

One can also discern individual states' contributions to the overall state income mobility from cumulative changes in each state's per capita income ranking (five-year rolling-origin) (Figure 4). Wyoming and North Dakota experienced the most significant ups and downs in their per capita income rankings. On the other hand, some the richest and poorest states such as Connecticut, New Jersey, Mississippi and Arkansas have been stable in their rankings. Figure 4 also shows whether a given state's rank mobility is the result of a long-run upward or downward shift in its income ranking. Some New England states, such as New Hampshire (up from rank 21st to 6th between 1995 and 2003) and Vermont (35th–20th), have been 'upward-mobile,' reflecting the New England 'turn around' during the 1980s (Fan and Casetti, 1994). High-growth states such as Virginia (31st–9th) and Colorado (20th–7th) also show overall upward mobility. States that are generally characterised as 'downward-mobile' include Montana (down from 18th to 42nd), Oregon (13th–29th) and Nevada (1st–17th).

Third, in terms of spatial clustering, Figure 5 shows plots of Moran's I spatial autocorrelation statistics, using binary contiguity as the basis of a spatial weighting matrix ('contiguity matrix'), essentially replicating the results of Rey and Montouri (1999). The figure also shows Moran's I using a spatial weighing matrix based on physical distance between states ('distance matrix'). There is strong evidence of spatial autocorrelation, as the Moran's I statistics are significant at $P = 0.05$ for all years, with the only exception of four years (1978–81) for the distance matrix.[6] There are additional years, 1975–1977 and 1981–1983, in which Moran's I are significant at $P = 0.05$, but not at $P = 0.01$. The figure shows that the evolution of state income distribution is consistently clustered spatially, but the levels of spatial dependence seem to vary systematically over time. Both trajectories of the Moran's I based on the two weighting matrices show a relative stability until the early 1970s, followed by a rapid decline during the 1970s.[7] The trend then reverses in 1981, and the statistic

5 The actual correlation coefficient between the two indices is −0.782 because a larger income class (Shorrocks) mobility index indicates higher mobility whereas a larger income rank (Kendall) mobility index indicates lower mobility, but clearly the two types of mobility are positively correlated.

6 An analysis of income values, using Shapiro–Wilk's test for normality, reveals that the US data violate the normality assumption for 2001, 2002 and 2003 only at $P = 0.05$. Therefore, following Rey and Montouri (1999), I base the significance test on the randomization assumption for both countries for all years, involving 1000 random permutations.

7 The difference between the trajectories of Moran's I based on the contiguity and distance matrices is probably the result of large differences in distances among states in the USA. Large Western states and small New England states would have markedly different numbers of 'neighbours' based on the two weighting matrix schemes. For example, Colorado has seven contiguous-neighbours (including Arizona, where the corner is touched), and has eight distance-neighbours (South Dakota is the only additional neighbour). On the other hand, Massachusetts has five contiguous-neighbours, but has 12 distance-neighbours.

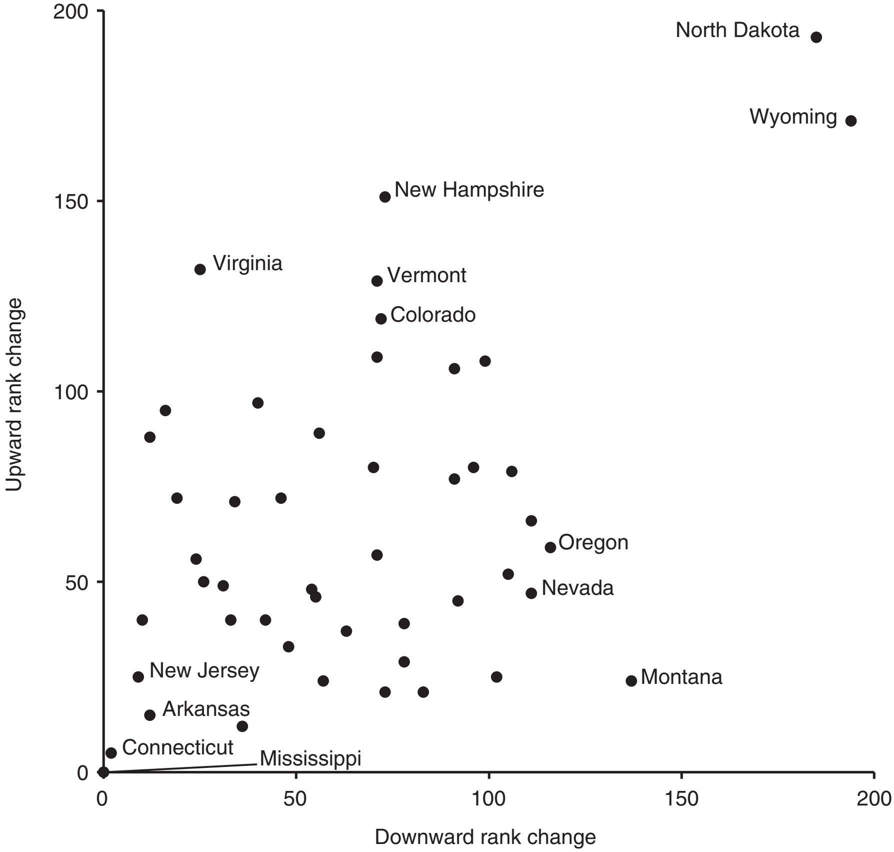

Figure 4. Cumulative per capita income rank changes for US states, 1955–2003. The value indicates the sum of a state's per capita income rank changes, either upward (on vertical axis) or downward (on horizontal axis), at rolling five-year intervals.

increases until 1989. Slow decline takes place throughout the 1990s, and there is an apparent, small increase between 2000 and 2003. At the state-scale, there appears no secular trend in spatial dependence during the study period.

Three observations are worth highlighting within the US state-scale income disparities between 1955 and 2003. First, a clear convergence is attributable primarily to the pre-1970s inequality trends, and the post-1970s trajectory shows little sign of further convergence as well as the presence of two temporary divergence episodes in the late 1980s and 1990s. Second, the two divergence episodes accompanied dissimilar changes in other dimensions of disparities: mobility (high in the 1980s and low in the 1990s) and spatial dependence (surge in the 1980s and little change in the 1990s). The differences imply that underlying mechanisms behind the two episodes may differ. Third, little evidence shows secular changes in any of these disparity dimensions at the state scale from the 1970s. This observation contrasts, for example, with some globalisation hypotheses which often imply certain secular trends in regional economic disparities, such as increasing instability and worsening inequality.

To build on and gain further insights into these state-scale observations, the next sections establish stylised facts about the evolution of multi-dimensional income

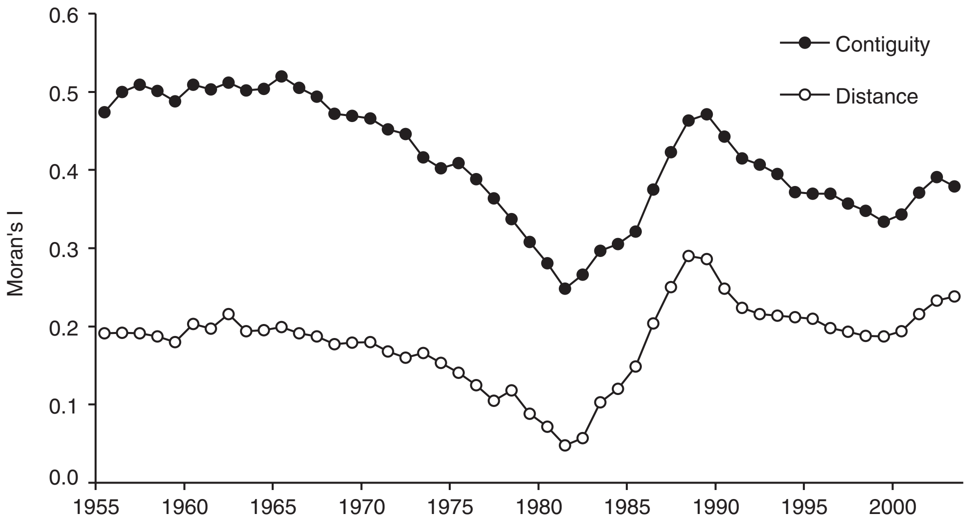

Figure 5. Spatial autocorrelation (Moran's I) of state per capita income based on two spatial weight matrices (contiguity and distance), 1955–2001.

disparities at multiple spatial scales. The analysis will not only help identify the scale(s) at which key driving forces of spatial disparities operate (e.g. a secular trend may be found below or above the state scale), but will also improve our understanding of the contributing processes to the evolution of the US regional income disparities more generally, including the underlying reasons of the two divergence episodes.

3. Methods and data

3.1. Two approaches to scalar effects

There are two main ways to analyse spatial phenomenon at multiple scales (Wu et al., 2000). The first is to systematically repeat a method, originally developed to examine a phenomenon at a single scale (e.g. inequality index), to multiple scales. This approach requires different data sets to be prepared for each scale. The second approach is to use methods specifically designed to examine the relative significance of different scales on various socioeconomic phenomena. This approach uses inherently multi-scale methods, such as scale variances, semi-variances and inequality decomposition techniques. These methods use the smallest-scale data combined with information about the nested regional hierarchy.

This article first presents results from the repeated applications of single-scale methods, including inequality indices, kernel density estimation, mobility statistics and spatial autocorrelation statistics, which are well documented in the convergence literature [e.g. Firebaugh (2003) for inequality indices, Quah (1997) for kernel density estimation, Rey (2004b) for mobility statistics and Rey and Montouri (1999) for spatial autocorrelation statistics]. Following the results of the repeated single-scale analysis, I present results from the multi-scale method [i.e. scale variance analysis (Moellering and Tobler, 1972)] that enables me to determine the relative variability of regional income at each spatial scale in a nested hierarchical regional system.

3.2. Scale variance

The scale variance method is described in detail in Moellering and Tobler (1972), and is summarised in the following illustrative example of scale variance for a nested three-level regional system consisting of census district- (α), state- (β), and county (γ)-level scales:

$$X_{ijk} = \mu + \alpha_i + \beta_{ij} + \gamma_{ijk} \tag{1}$$

where X_{ijk} is the value (e.g. per capita income) of the kth county of the jth state of the ith census district. This value is expressed as a combination of the overall mean over the entire data set (μ), and the effects at each of the three scale levels, α_i, β_{ij}, and γ_{ijk}. This model has no error term because it assumes census-type data. Each of these effects may be described in terms of X as:

$$\begin{aligned} \mu &= \bar{X}\ldots \\ \alpha_i &= \bar{X}_i.. - \bar{X}\ldots \\ \beta_{ij} &= \bar{X}_{ij}. - \bar{X}_i.. \\ \gamma_{ijk} &= X_{ijk} - \bar{X}_{ij}. \end{aligned} \tag{2}$$

where

$$\begin{aligned} \bar{X}\ldots &= \frac{\sum_i \sum_j \sum_k X_{ijk}}{N} \\ \bar{X}_i.. &= \frac{\sum_j \sum_k X_{ijk}}{n_i} \\ \bar{X}_{ij}. &= \frac{\sum_k X_{ijk}}{n_{ij}} \end{aligned} \tag{3}$$

N is the total number of counties in the entire data set (i.e. country), n_i the number of counties in the ith census district and n_{ij} the number of counties in the jth state of the ith district. $\bar{X}\ldots$ indicates that this is the mean of X summed over the subscripts (dots). We can rewrite the original equation in terms of deviations from the means:

$$X_{ijk} - \bar{X}\ldots = (\bar{X}_i.. - \bar{X}\ldots) + (\bar{X}_{ij}. - \bar{X}_i..) + (X_{ijk} - \bar{X}_{ij}.) \tag{4}$$

When this equation is squared, the covariance terms drop out, and summing over all subscripts results in:

$$\begin{aligned} \sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{k=1}^{K_{ij}}(X_{ijk} - \bar{X}\ldots)^2 = &\sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{k=1}^{K_{ij}}(\bar{X}_i.. - \bar{X}\ldots)^2 + \sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{k=1}^{K_{ij}}(\bar{X}_{ij}. - \bar{X}_i..)^2 \\ &+ \sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{k=1}^{K_{ij}}(\bar{X}_{ijk} - \bar{X}_{ij}.)^2 \end{aligned} \tag{5}$$

where I is the number of census districts in the country, J_i is the number of states in each Census district i, K_{ij} is the number of counties in each state i in each district j. Notice the difference between the two sets of numbers, [N, n_i, n_{ij}] and [I, J_i, K_{ij}]; the former includes the number of the smallest spatial units at each level (i.e. counties in

Table 2. Mean square estimates and scale variance components

Scale	Degrees of freedom	Mean square estimate	Scale variance component
α	$I-1$	$\frac{SS_\alpha}{I-1}$	$\frac{\sum_{i=1}^{I}(\bar{X}_{i}..-\bar{X}...)^2}{I-1}$
β	$\sum_{i=1}^{I}(J_i-1)$	$\frac{SS_\beta}{\sum_{i=1}^{I}(J_i-1)}$	$\frac{\sum_{i=1}^{I}\sum_{j=1}^{J_i}(\bar{X}_{ij}.-\bar{X}_{i}..)^2}{\sum_{i=1}^{I}(J_i-1)}$
γ	$\sum_{i=1}^{I}\sum_{j=1}^{Ji}(K_{ij}-1)$	$\frac{SS_\gamma}{\sum_{i=1}^{I}\sum_{j=1}^{Ji}(K_{ij}-1)}$	$\frac{\sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{k=1}^{K_{ij}}(X_{ijk}-\bar{X}_{ij}.)^2}{\sum_{i=1}^{I}\sum_{j=1}^{J_i}(K_{ij}-1)}$

the country, counties in each district and so on), while the latter includes the number of the next-lower spatial units (i.e. districts in the country, states in each district and so on). This equation shows that the total sum of squares can be partitioned into three parts, each attributable to one-scale level:

$$SS_{\text{total}} = SS_\alpha + SS_\beta + SS_\gamma \tag{6}$$

Dividing these partitioned sums of squares by their respective degrees of freedom results in the corresponding mean square estimates (Table 2). Moellering and Tobler (1972) show that the respective scale variance components can be derived from the sums of the squared deviations.

3.3. Data

For income data, I use regional average per capita income that consists of the income accrued from participation in production, from both government and business transfer payments, and from government interest, from the U.S. Bureau of Economic Analysis. The base data set covers 48 states and counties within those states (District of Columbia is excluded from all analyses). To eliminate the effects of rising averages over time, I use relative income that is a division of each region's income level by the overall average of all regions' income levels at a given year. The issue of differential inflation rates and purchasing powers *across regions* presents a major challenge in regional convergence studies. Price levels and their rates of change clearly differ across space even within a country (e.g. between urban and rural, and between north and south). Sahling and Smith (1983) has shown, for example, that per capita income gap between the US North and South is not very significant when adjusted for costs of living (see also, Eberts and Schweitzer, 1994). Yet, unlike national income data, for which purchasing power parity (PPP) data are increasingly being facilitated, we do not have reliable and comprehensive regional PPP data at state or sub-state scales in the USA, forcing me to resort to unadjusted regional income data.[8]

8 Some attempts have been made to estimate purchasing power-adjusted, or price-adjusted regional income data (e.g. Mitchener and McLean, 1999), but available data are insufficient in their regional and temporal coverage. The Bureau of Labor Statistics also provides costs of living indices data for selected metropolitan areas, but again they have insufficient coverage.

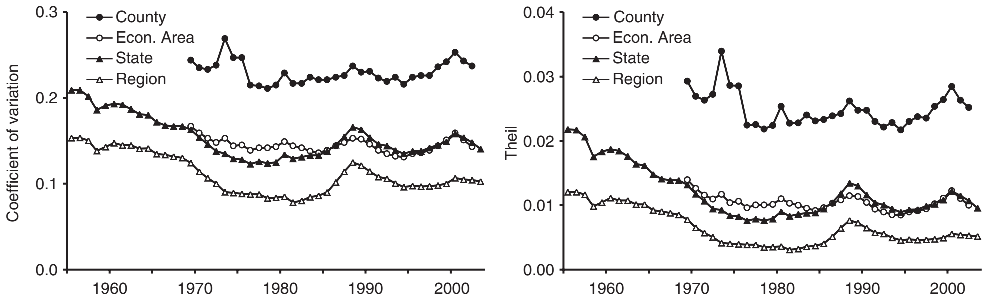

Figure 6. Spatial income inequality at four scales in coefficient of variation and Theil index, 1955–2003.

In addition, there is an issue of weighting data. In the international context, Firebaugh (2003) shows that weighting income inequality indices by national population makes a crucial difference in our understanding of global income inequality (see also, Dunford, 1993; Sala-i-Martin, 2002). In regional context, Tortosa-Ausina et al. (2005) apply demographic weighting not only to income inequality indices, but also to the analysis of transition matrices and density functions, in their study of convergence across Spanish provinces (see also, Alasia, 2001). While being aware of this issue, this study uses unweighted income data to keep its focus on scalar effects.

4. Scalar effects: repetition of single-scale method

The application of repeated single-scale analyses to US regional income disparities reveals several stylised facts. First, there has been a downward shift in scale at which spatial income inequality is pronounced ('downscaling' of spatial inequality) in the past few decades. Second, little evidence shows polarising or stratifying regional income levels at any observed scales; rather, increased inequality at the county scale has been driven by a small number of super-rich counties. Third, relative positions of regional income levels, measured by mobility indices, have become more solidified during the 1990s than during the previous two decades at all scales. Fourth, there is a relatively secular trend of spatial fragmentation in county scale income distribution from the end of the 1960s, which indicates that neighbouring counties are increasingly differentiated in per capita income terms. Finally, these findings also suggest qualitative differences in the temporary divergence episodes in the late 1980s and 1990s.

4.1. Inequality indices and convergence

To examine trajectories of spatial income inequality at multiple scales, I plot the CV and Theil indices for four scales, including 'region' defined by the Bureau of Economic Analysis ($n = 8$), state ($n = 48$), BEA economic area ($n = 170$) and county ($n = 3078$) (Figure 6). Economic area data are constructed using county income and population data, and both are available annually from 1969 to 2002. Several characteristics emerge upon a visual inspection of the trajectories of the inequality indices. First, the difference between the two indices is relatively insignificant, compared with the differences across scales, thus the choice of index seems to make little difference

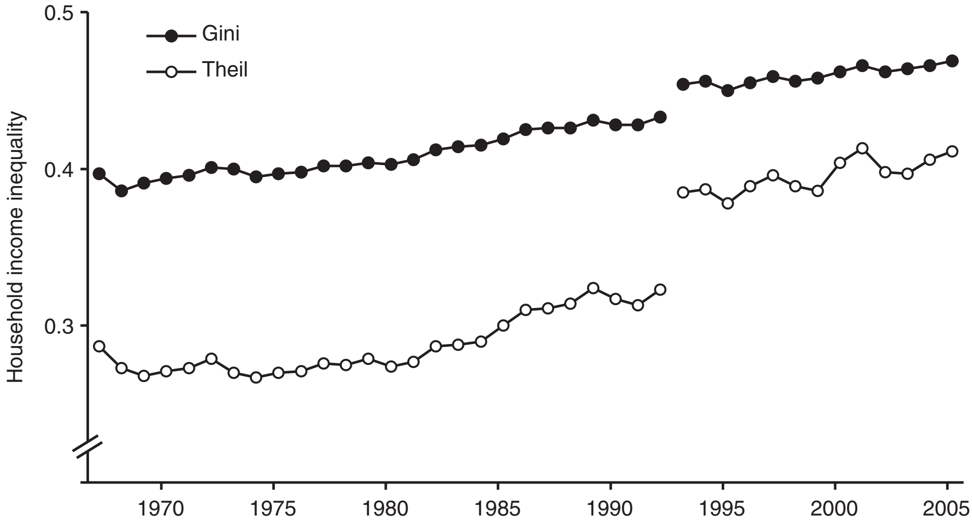

Figure 7. Household scale income inequality in the USA, 1967–2005. Direct comparisons of data before and after 1993 are not recommended because of substantial methodological changes in the 1994 Annual Social and Economic Supplements (U.S. Census Bureau, 2006, p. 8). *Source*: U.S. Census Bureau (2006).

on observation. Second, these inequality indices do not show a secular increase, or decrease, at any scales during the study period. In particular, the county-level inequality indices fluctuate without a clear upward or downward trend over the 33-year period. Third, shapes of inequality trajectories differ across scales. The county-level index shows a surge in inequality around 1974, but such a temporary divergence is barely visible at other scales. Fourth, perhaps most importantly, there appears to be systematic differences in the trajectories of the two temporary divergence episodes in the 1980s and the 1990s across scales. At the region scale, the Theil index in 2000 (the second peak of inequality) is 73% of the 1988 level (the first peak). At the state, economic area and county scales, the equivalent ratios are 91, 107 and 109%, respectively, showing systematic patterns where smaller scales are showing comparatively higher spatial inequality between the two periods. In other words, the temporary divergence in the 1980s seems to be characterised by strong income differentiation at larger scales, such as multi-state region and state, while another episode of temporary divergence in the 1990s is influenced more by the trend at smaller scales, such as county and economic area.

The observation of the regional income inequality patterns naturally raises a question whether we can attribute the systematic 'downscaling' of income inequality to the smallest scale, individual or household scale. Figure 7 shows two inequality indices, Gini and Theil, based on US household income data between 1967 and 2005 (U.S. Census Bureau, 2006). Two trends are evident. First, the household income inequality has been on the rise with few interruptions at least since the mid-1970s. Second, unlike the regional income inequality patterns, the household income inequality does not show clear two peaks during the late 1980s and 1990s; hence, does not follow the systematic patterns that are evident in regional income inequality trends.

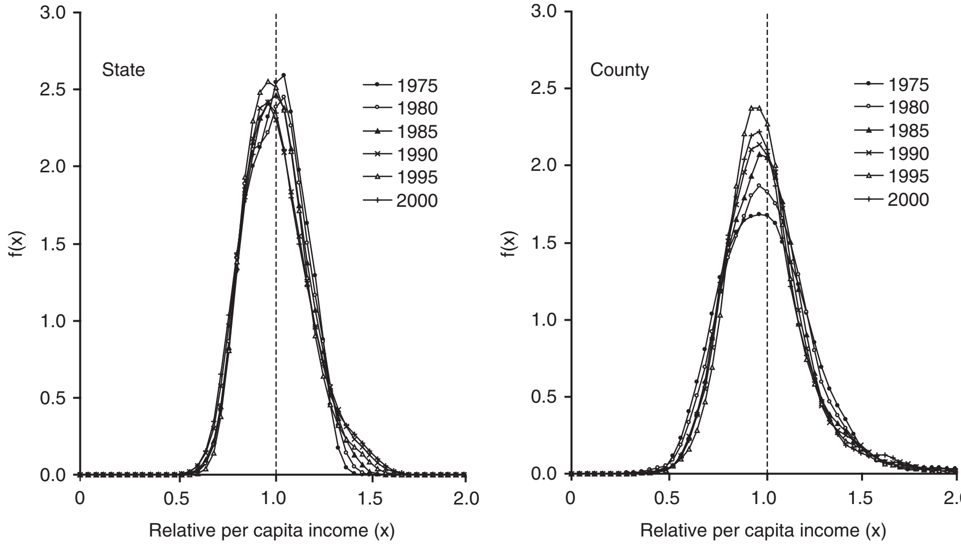

Figure 8. Distributional evolution of per capita income at state and county scales, 1957–2005. Probability density curves are shown for relative per capita income level at five-year intervals.

4.2. Modality and churning

We can also observe the effects of different scales on deciphering convergence patterns from the morphological characteristics of county per capita income distribution, as probability densities, between 1969 and 2001 (Figure 8). There is no evidence of clear polarisation or stratification of spatial income distribution at the county scale. We do observe, however, that at the county scale, there was much more significant change in the shape of the density curve than at the state-scale between 1969 and 2001. The peak of the curve narrows in a relatively short time period, suggesting the convergence of county income levels around the mean, although inequality level has not lowered much during the same period (Figure 6). This is due to a small number of counties becoming extraordinarily high income in the recent years as seen in the extending upper tail on the curve.

Figure 9 shows trajectories of income class and rank churning, using the Shorrocks index and Kendall's τ-statistic respectively, at three scales (state, economic area and county).[9] The shapes of the mobility indices are generally similar across scales for both class and rank distribution. The 1970s and 1980s show higher mobility than the 1990s, confirming that the most recent decade is characterised by relative stability of regional income class and rank relations at scales smaller than state. This trend contrasts with a popular perception of increasingly destabilised regional economic system in the period of globalization.

9 Income classes for the Shorrocks index are based on the initial year's income distribution (1955 for state, and 1969 for economic area and county). Mobility indices for the region scale are not shown because the small number of units makes these indices less meaningful.

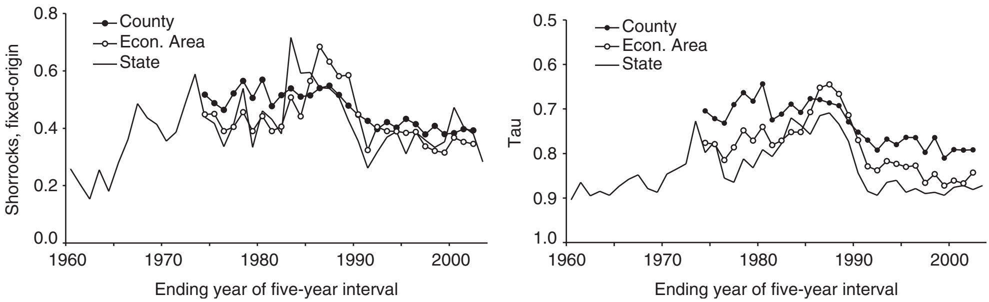

Figure 9. Mobilities of regional incomes at county, economic area and state scales in Shorrocks (class mobility) and Tau (rank mobility) indices, 1955–2003, at five-year intervals.

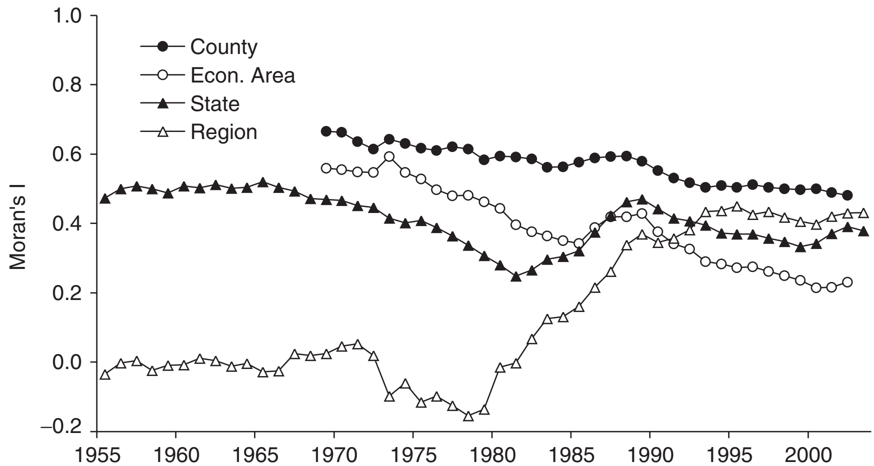

Figure 10. Spatial autocorrelation (Moran's I) of per capita income at four scales, 1955–2003.

4.3. Spatial dependence

Moran's I-statistic based on contiguity matrices are plotted for multiple scales (Figure 10).[10] Moran's I at the region scale is statistically significant only between 1993 and 1997, at the $P = 0.05$ level. All other scales show statistically significant Moran's I at the $P = 0.05$ and 0.01 levels in all years. Because the values of Moran's I are influenced by the number of regional units, the main concern is the shape of each spatial dependence trajectory, rather than the absolute values of the statistic.

The state-scale trends are not replicated at the other scales. The timings of the 'dip' in the statistics differ at the state (1981) and economic area (1985) scales. At the county scale, such a 'dip' is not clearly visible. The 1970s shows declining Moran's I-values at

10 Some US counties are islands that are not contiguous to any other counties and municipalities, respectively. For those cases, I define 'ad hoc' spatial contiguity by bridges and major ferry routes. For the USA, I linked the following sets of counties: San Juan (WA) with Skagit (WA), Nantucket (MA) with Barnstable (MA) and Richmond (NY) with Middlesex (NJ), Union (NJ), Hudson (NJ) and Kings (NY).

all scales, and the 1990s also shows declining values at all scales except for the region scale, whose value is not statistically significant. These two decades can thus be considered as the periods of spatial fragmentation of regional economies. Between these two decades of secular decline, however, the 1980s appears to be the period of change. It shows a steadily increasing Moran's I at the state-scale, while the economic area-scale trend reverses in the mid-1980s, and the county-scale statistic remains more or less constant. Therefore, depending on which scale is observed, the interpretation of the spatial dependence trend will vary for this time period, but it seems clear, at least, that regional income distribution has been increasingly fragmented spatially at smaller scales, especially at the county scale, creating salt-and-pepper-like patterns of income levels if mapped on a choropleth map.

5. Scalar effects: scale variance

Rather than repeating a single-scale method at different scales, this section examines scalar effects using scale variances that enable me to determine the relative variability of regional income at different scales that are hierarchically nested. With a small methodological adjustment to redefine some boundary definitions, I conduct the scale variance analysis at four and five spatial scales. The analysis confirms the rising significance of smaller scales in regional income disparities. Furthermore, the scale variance analysis exposes another stylised fact: an increasing importance of the urban–rural difference in regional income dynamics in the recent decades.

5.1. Nesting regions

Calculation of scale variances requires hierarchically nested regional structures, but regional boundaries at which income data are collected are not always nested in such a way. Counties are completely nested in a state (i.e. no county crosses a state border), but metropolitan statistical areas are not (i.e. some metropolitan statistical areas cross a state border). This requirement limits the use of some potentially interesting sets of spatial scales. In particular, there are relatively few appropriate spatial scales between state and county (i.e. those that nest counties and are nested in a state), which fill the large gap in the numbers of counties (over 3000 counties) and states (48 contiguous states).

I deal with this problem by creating 'quasi-regional boundaries' that completely nest lower-scale boundaries, in order to conduct a scale variance analysis at similar scales to those in the previous sections. Among the four scales (region, state, economic area and county), a state does not necessarily nest economic areas. Consequently, a region does not necessarily nest economic areas (although it nests states). I, thus, create quasi-state and quasi-region boundaries that nest lower-level scales completely while resembling their original shapes as closely as possible.

Quasi-state and region boundaries are reconstructed by aggregating multiple economic areas based on a simple rule. When an economic area is completely contained in a single state, the economic area belongs to the state. When an economic area crosses state border(s), the economic area is assigned to a state that has the largest areal portion of the economic area. This process yields 43 quasi-states, five states down from the original 48 states because some small New England and Mid-Atlantic states become a single quasi-state (Figure 11). There is also one quasi-state ('quasi-Kentucky')

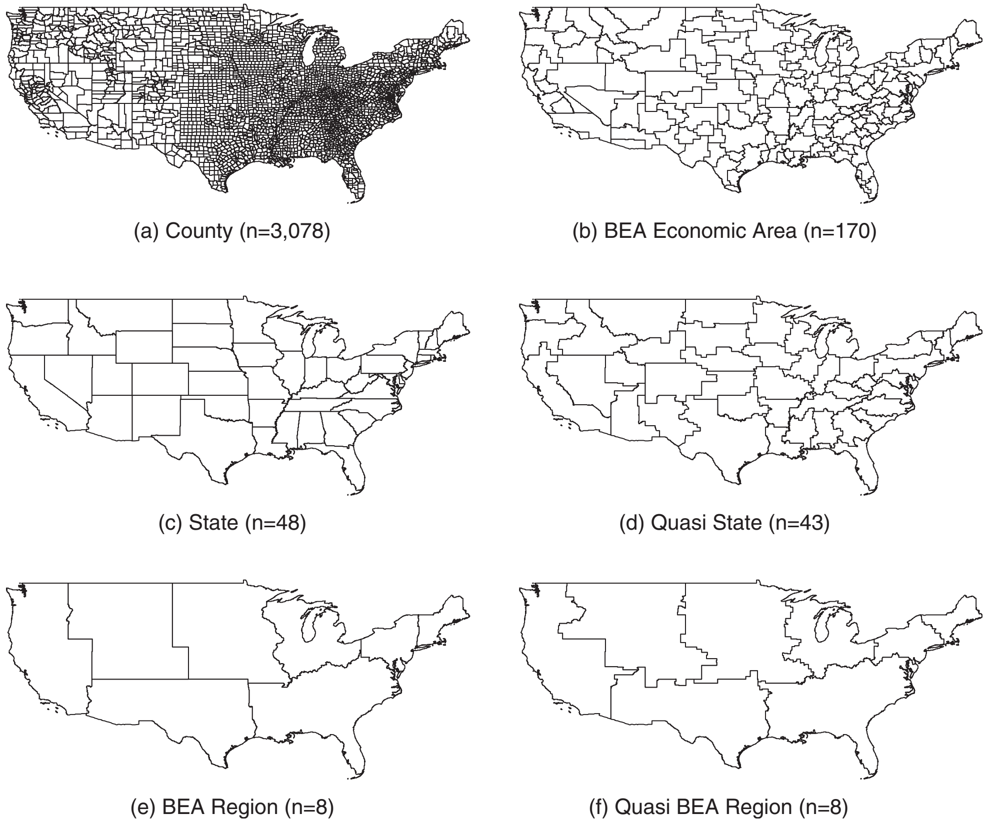

Figure 11. Hierarchical scalar structure in the USA for scale variance analysis. Counties, BEA economic areas, Quasi-states and Quasi-BEA regions are completely nested in their upper-level scales.

that has two separate areal portions. I maintain these two areal portions as a single state without any modifications. Quasi-regions are constructed in the same manner; each state is assigned to a region that has the largest areal portion of the state. This process results in eight quasi-regions.

5.2. Scale variance changes

Trajectories of scale variances, and of percent sums of squares, are presented for the four scales (Figure 12). First, the county scale consistently shows the highest scale variance throughout the study period, indicating that the largest income variation occurs at the smallest scale. The county-scale variance is also increasing, most steadily between 1978 and 2000. The increasing importance of the county scale *relative to* the other scales is more clearly visible in the trajectories of the percent sums of squares, where the county-scale value has risen nearly by 20% during the study period, primarily at the costs of the region-scale values.

Second, the region scale shows rapidly declining scale variances in the 1970s, followed by a temporary surge in the late 1980s. The initial scale variance in 1969 is nearly high enough to match that of the county scale. The declining variance in the 1970s coincides

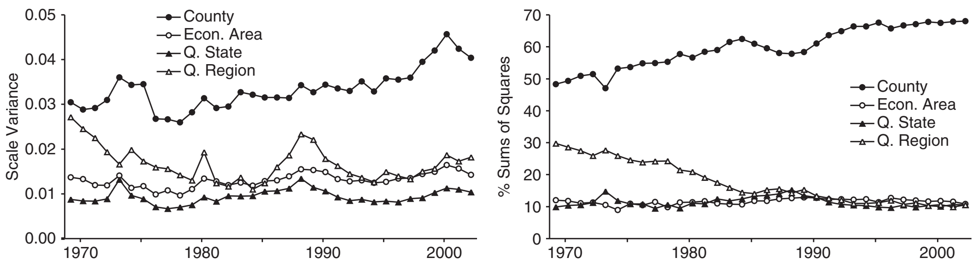

Figure 12. Scale variances and percent sums of squares based on per capita income at four spatial scales, 1969–2002.

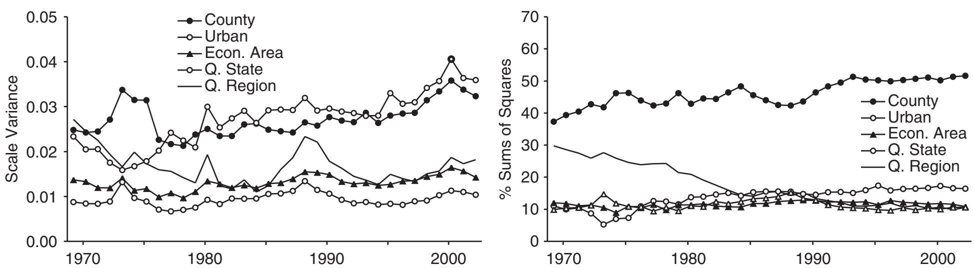

Figure 13. Scale variances and percent sums of squares based on per capita income at five spatial scales, 1969–2002.

with the period of post-war industrialisation in the US South. The temporary rise in variance in the late 1980s coincides with the period of temporary divergence at the region scale (Figure 6).

Third, there are two notable 'peaks' in the scale variance trajectories at the county scale, in the mid-1970s, and around 2000. The two peaks indicate periods when the income variation among counties within an economic area increased particularly rapidly. When these two peaks are compared with the trends of inequality indices (Figure 6), the timing of the peaks match across the two methods, although another rise of inequality around 1988 is not as clearly visible in the scale variance trend.

Fourth, in contrast to the county-scale variance, the state-scale variance is consistently low. Although the low variances may be partly explained by the use of quasi-state definitions, it still appears that states are not necessarily the best regional definitions to capture spatial income differences. This finding is suggestive for the contemporary convergence literature, which often uses states as the main and the only spatial unit of regional income analysis.

In addition to the above four-scale schemes, I also conduct a scale variance analysis with another scale based on 'urban–rural' differences (Figure 13). This urban–rural scale (hereafter 'urban' scale) differs from the previously defined other scales because it is essentially an artificial construct, and is not intended to resemble actual regional definitions, as I have done with the quasi-regional scales. Within each economic area, there are metropolitan counties and non-metropolitan counties. I combine all metropolitan counties within an economic area as 'urban' area, and all non-metropolitan counties as 'rural' area, resulting in one urban area, one rural area or both in each economic area.[11] There may be only an urban area or rural area, because some economic areas consist only metropolitan counties or non-metropolitan counties.[12] This process yields 320 areas at the urban-level scale (a little less than twice the number of economic areas (170) because of 20 purely urban or purely rural economic areas). Because there are at the most two areas, urban and rural areas in each economic area, scale variance at the urban scale only detects variance attributable to urban–rural differences (i.e. not urban–urban or rural–rural differences).

The addition of the urban scale affects the original trajectories of the county-scale variances significantly. It exceeds the county-scale trajectory in most years after 1980. The urban scale seems to affect differentially the two peaks of county-scale variance in the mid-1970s and around 2000. Until the late 1970s, scale variances at the county- and urban scales appear to move somewhat independently. In particular, the rise of variance at the county scale in the mid-1970s accompanies a lowering urban-scale variance. In contrast, since the early 1980s, scale variances at these two scales move more or less uniformly. Subsequently, the rise in county-scale variance around 2000 accompanies a simultaneous rise in urban-scale variance. In terms of the relative importance of each scale, represented by the percent sums of squares, the country scale remains the most important, but the urban scale replaces the region scale as the second most important scale in 1982.

6. Discussion

The exploratory nature of this study does not allow for a formal test of theories such as (Stolper–Samuelson variant of) globalisation and skill-biased technical change hypotheses that are often used to explain the steady increase in individual/household income inequality (Storper, 2000; Moore and Ranjan, 2005). It is possible, therefore, that the apparent lack of further regional income convergence since the 1970s is also partly affected by one or both of these factors. For example, rising importance of urban–rural division in the scale variance analysis is consistent with the view that urban areas are typically better endowed with human capital (skilled workers), which would be favoured by skill-biased technical changes. It should be noted, however, that these theories alone may not be sufficient to account for the historical evolution and the scalar aspects of the US spatial income disparities. Most notably, the two episodes of temporary divergence since the 1970s are unlikely explained solely by these hypotheses that focus on relatively secular structural changes. Furthermore, these theories do not directly account for the other empirical observations in this study such as increasing spatial fragmentation of income levels at the county scale and the varying regional income class/rank mobility over the past few decades.

Subsequently, I offer a speculative account of the observed spatial income disparities that emphasises the increasing importance of the financial realm of the economy, rather than the structural changes in the real economy (e.g. increased global commodity

11 Even if there are multiple metropolitan statistical areas (MSAs) in one economic area, all counties in some MSAs are considered to be part of a single 'urban' area.

12 Metropolitan areas are based on the 1999 definition by the Office of Management and Budget. BEA defines 'non-metropolitan nodes,' which are not defined as metropolitan areas by OMB, but are considered to have nodal functions within an economic area. The analysis presented here does not include non-metropolitan nodes in metro-areas.

trade and technological change). This view extends on Galbraith and Hale (2004), who suggest that the information technology bubble of the 1990s had a major effect on the spatial distribution of the income in the USA. The global economy has been increasingly driven by financial trade rather than by commodity and service trade since the 1970s, and that this trend accelerated after wide-ranging financial liberalisation in the 1980s. The recession beginning in the fourth quarter of 1990 in the USA was the first recession since financial liberalisation, and differed fundamentally from the previous recessions (Miyazaki, 1992). This 'new' recession was preceded by a stock market crash on 19 October 1987, rather than by emerging insufficient effective demand (e.g. excessive inventories, and the rise in wages or prices). In this new type of recession, the adjustment process of financial assets induced the recession in the real economy through a credit crunch. A closer look at the regional inequality patterns in the USA shows that the rising inequality peaks in 1988, after the stock market crash in 1987, but before the beginning of contraction in the US business cycle in 1990. In addition, the divergence in the late 1990s also peaks in 2000, the year that the so-called 'dot-com' stock market crash (the NASDAQ composition index reached its peak on 10 March 2000), but before the peak of the business cycle (first quarter of 2001).

Looking beyond the timing of the two divergence episodes, the differences between the two episodes seem attributable to distinct geographies of financial bubbles in the 1980s and the 1990s. During the 1980s, real estate investment played a major role in the creation of the financial bubble, and one of its major destinations was the northeast region, where critical functions of the emerging global political economy were clustered (e.g. finance in New York, education in Boston and politics in DC). As the result of excessive commercial office development, nevertheless, a large amount of bad loans in real estate, and bank failure cases, abounded in the northeast by 1991 (Miyazaki, 1992). Unlike the 1980s situation, the financial bubble in the late 1990s involved speculative investment in a wide range of internet-based, 'dot-com' businesses. Dot-com businesses were deemed more locationally flexible in the sense that the destinations of venture capital investments were not limited to a few world-cities, but included many second-tier metropolitan areas such as San Francisco, Seattle, Denver and Austin (Zook, 2005).

The distinct natures of financial bubbles during the 1980s and the 1990s, and their geographies are consistent with the apparent scalar dynamics of regional income disparities at least in three respects. First, they emulate the cross-scalar shift in the temporary divergence episodes, where divergence is increasingly more pronounced at smaller scales (such as county and metropolitan scales) in the late 1990s than in the late 1980s. Locally oriented nature of venture capital investment during the dot-com boom (Zook, 2005) may underlie the increased income disparities among places at sub-state scales. Second, the divergence of the late 1980s accompanied spatial consolidation of regional incomes, while that of the late 1990s accompanied continuing fragmentation that again seems to have resulted form the cross-scalar shift. Third, the observed patterns are also consistent with the view that the acceleration of financial liberalisation, a symbolic feature of contemporary globalisation, does not necessarily destabilise existing regional structures; rather it resulted in the disproportionate growth of a few global and regional financial centres. It may be that the 'windows of locational opportunities' (Storper and Walker, 1989) were relatively open during the 1970s and the early 1980s, but increasing global economic integration may present rather dim opportunities for poorer regions to surpass richer regions in their income levels.

7. Conclusions

This article has provided new stylised facts about the scalar aspects of multi-dimensional regional income disparities that must be accounted for in future research on the US regional inequality and convergence. It has shown that one cannot infer the evolution of US regional income disparities at different scales by looking at those only at a single scale, confirming the views of Martin (1999) and Overman (2004). In particular, sub-state scales seem to have become important scales at which to analyse US regional income disparities. The exploratory approach has allowed the speculation that the geography of income disparities reflects not only secular structural shifts in the real economy, but are also significantly affected by the cyclical financial sphere of the economy. Future studies might pursue more rigorous causal analysis of spatial income disparities and financial dynamics, while enhancing analytical approaches such as the development and use of income data that are adjusted for cost-of-living differences (cf. Sahling and Smith, 1983) and the inclusion of sub-county scale income data (cf. Massey and Fischer, 2003).

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