Spatial Dependence in the Evolution of Regional Income Distributions[1]

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Abstract

This paper introduces three measures of spatial dependence for use in the analysis of regional income distributions and their evolution. The first builds upon the notion of regional conditioning (Quah, 1993), and is derived as a trace statistic from a modified Markov transition matrix. The remaining two statistics are intended for use in a dynamic context and measure the degree of spatial clustering and regional cohesion in income rank mobility. All three measures are applied in an empirical analysis of per capita income patterns in the lower 48 United States over the 1929-99 period.

1 Introduction

The question of regional economic convergence continues to attract much attention (Cuadrado-Roura et al., 1999; Kim, 1998; Nijkamp and Poot, 1998; Tsionas, 2000). This rich and growing literature contains a number of fascinating debates surrounding the theories of spatial economic growth and change, as well as the appropriate empirical strategies that can be used to confront these theories (Sala-i-Martin, 1996).

On a theoretical front, the main competitors appear to be the traditional neoclassical growth paradigm (e.g., Barro and Sala-i-Martin (1991)) and the more recent arrival, endogenous growth theory (e.g., Aghion and Howitt (1998)). When applied to the question of regional growth and change, the two perspectives generate radically different policy implications. The neoclassical approach predicts eventual convergence due to the presence of diminishing returns to capital. Accordingly, because the convergence process will operate to reduce initial income differentials, policy interventions to correct the latter are viewed as unnecessary. Endogenous growth theory tells a very different story. The presence of increasing returns to scale leads to the possibility of persistent and even widening levels of regional income disparities. While this would appear to make a strong case for policy interventions, endogenous growth theorists are quick to point out the enormous problems associated with information, coordination and the question of the proper geographical scale to use in designing appropriate policies (Bröcker, 1997). Beyond the policy debates, much interest centers on the convergence hypothesis as a vehicle to differentiate between these two competing approaches towards economic growth (Sala-i-Martin, 1996).

While both theories do touch on the spatial dimensions of regional growth processes, a number of authors have argued that much more needs to be accomplished in this regard before the promise of the theories is fully realized (Nijkamp and Poot, 1998; Oosterhaven, 1997). At the same time, the issues associated with spatially referenced data that are at the heart of empirical analyses of the convergence hypotheses are also beginning to attract increased attention (Kelejian et al., 1997; López-Bazo et al., 1998; Rey and Montouri, 1999; Magalhães et al., 2000).

This paper takes up the latter area of concern and examines the role of spatial dependence in a class of models for regional income convergence that have been recently suggested in the literature. It introduces several new measures for spatial dependence in regional income distributions and their dynamics. These measures are extensions of recent work reported in Rey (2001) for the analysis of spatial dependence in regional growth and change. While the substantive focus is on the question of regional income convergence, the methodological issues examined appear to have relevance for the study of a wide class of phenomena that have spatial and temporal dimensions.

This paper is organized as follows. The next section provides a brief overview of the substantive issues surrounding convergence of regional income distributions. This is followed by a discussion of the role of spatial dependence in the analysis of regional income distributional dynamics. Section 4 introduces a number of new empirical measures designed to provide insights as to the role of spatial dependence in regional income growth and distributions. These methods are then applied in an empirical analysis of U.S. regional income growth patterns over the 1929-99 period, in section 5. The paper concludes with a summary of main findings and some directions for future research.

2 Distributional Dynamics

A number of recent studies have focused on the evolution of cross-sectional distributions in addressing the question of regional convergence (Ioannides and Overmann, 2000; Magrini, 1999; Overman and Ioannides, 1999; Quah, 1996b; Tsionas, 2000). The interest on distributional dynamics centers on several dimensions of regional evolutions. The first concerns the overall shape characteristics of the regional income distribution, primarily spread and skewness, and the evolution of these characteristics over time. The second dimension relates to the amount of internal mixing or rank mobility that occurs within these same distributions over time.

2.1 Morphological Characteristics

The morphology of the distribution can reveal important insights as to the current situation regarding regional income disparities. When viewed in a dynamic context, changes in the shape characteristics of these distributions can illuminate aspects of the regional growth processes. For example, figure 1 summarizes the evolution of the state income distributions at 10-year intervals beginning in 1929. The densities are generated for the lower 48 coterminous states using a normal kernel estimator.

Inspection of the densities reveals several important changes over this 71-year period. Perhaps most pronounced is the overall decline in the level of dispersion of the regional income distributions. The drop in dispersion is greatest between the 1939-1949 period and each additional decade yields

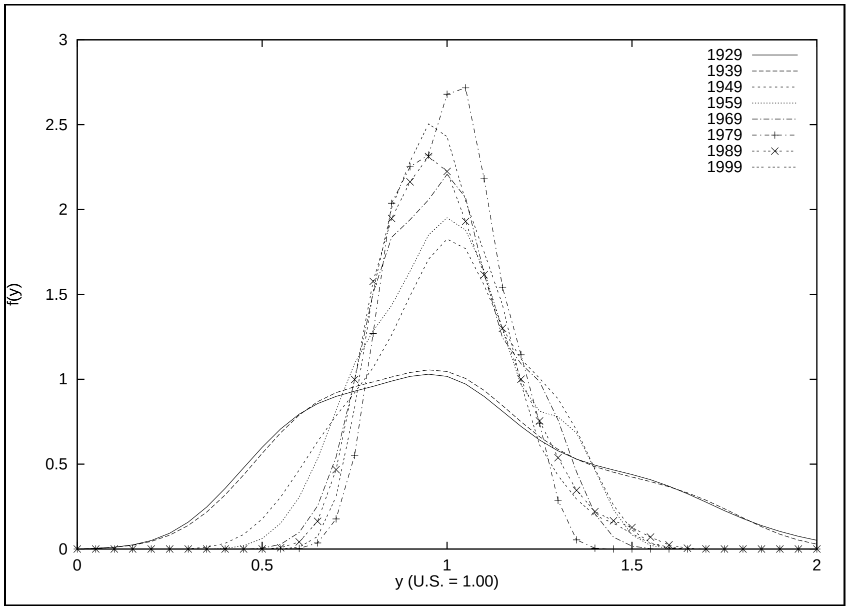

Figure 1: US Regional Per Capita Income Distributions 1929-99

a further reduction in spread with the exception of the 1979-89 period in which the situation was reversed. However, after 1989 the collapsing of the distribution appears to have continued.

It would also appear that several other characteristics of the distribution have changed over these decades. The first two densities display a higher degree of positive skewness than the later densities, although this is complicated by the radically different levels of variance over time. At the same time, a casual inspection suggests that the relative kurtosis in the distributions has changed over time, but here again the comparison is complicated by non-constant variances.

Figures 2 and 3 provide a more detailed annual view of these individual characteristics. The long term trend of so called σ-convergence is evident in figure 2, where the standard deviation of the relative incomes had steadily declined up until the late 1970's when the reversal noted above is reflected. While this increase in dispersion appeared to end by the late 1980's (see figure 1), there is some evidence of another shift towards increasing dispersion (divergence) towards the very end of the sample period.

Figure 3 plots measures of skewness and kurtosis for the distributions from each year. Because these measures are standardized against a normal

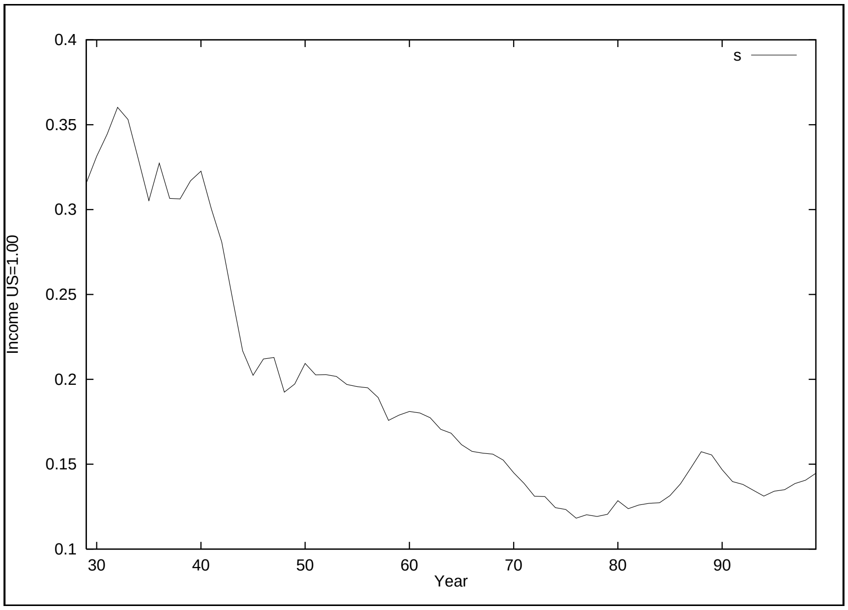

Figure 2: Dispersion: US Regional Per Capita Income Distribution 1929-99

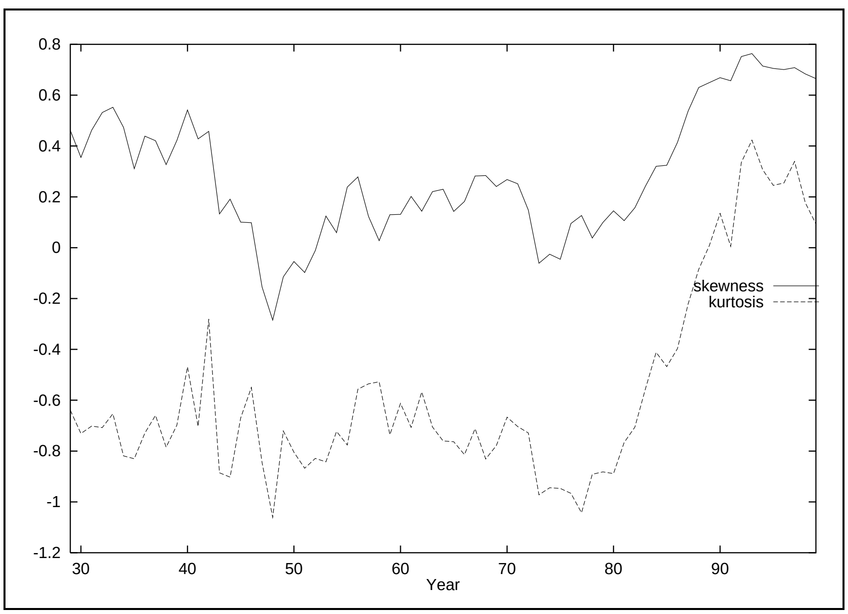

Figure 3: Skewness and Kurtosis: US Regional Per Capita Income Distribution 1929-99

distribution with the same variance of the distribution in question, the confounding effect of changing variance is controlled for here. These annual views reveal that the trends in these characteristics are much more mixed than is the case for dispersion. For example, skewness is positive and fluctuates around 0.40 until the mid 1940's at which point it begins a rapid decline that bottoms out in 1949. This period of decline in skewness coincides with the rapid decline in dispersion (convergence) from figure 2. In the middle portion of the study period the skewness is positive but generally lower than in the pre-1940 period. However, the middle 1970's through 1990 is a period in which the distribution becomes more positively skewed. Here again, this coincides with the turn around towards increased divergence in figure 2. Also during this period the kurtosis displays a strong increase above what was a negative value for most of the study period.[1]

Given the interest in the convergence hypothesis, much of the focus has been on how the measures of dispersion have changed over time. The evidence presented above, however, suggests that not only are measures of dispersion sensitive to regional convergence/divergence but higher order moments of the distribution may also signal changes in regional growth processes. In this regard, the use of kernel densities to trace out the evolution of the income distributions provides a powerful visualization framework, providing a flexible exploratory analysis perspective that complements more formal, theory based, econometric approaches that have dominated the convergence literature.

2.2 Class Mobility

Recent work on regional income dynamics has adopted Markov chain approaches to study the evolution of the regional income distribution over time (Quah, 1993, 1996a; Fingleton, 1999). At the core of these approaches is an empirical transition probability matrix:

$$M_{t,t+s} = \begin{pmatrix} m_{11} & \dots & m_{1k} \\ m_{21} & \dots & m_{2k} \\ \vdots & \vdots & \vdots \\ m_{k1} & \dots & m_{kk} \end{pmatrix} \tag{1}$$

where m_{ij} are the probabilities of a region making the transition from income class i to class j over the period t to $t+s$. The classes serve to discretize

[1]The increase moves the kurtosis of the distribution towards that displayed by a normal distribution.

Table 1: Estimated Annual Transition Matrix, US 1929-99

	Class				
n	0.59	0.79	0.89	1.10	∞
158	0.87	0.13	0.00	0.00	0.00
565	0.02	0.88	0.09	0.01	0.00
635	0.00	0.07	0.82	0.11	0.00
1409	0.00	0.00	0.05	0.93	0.02
593	0.00	0.00	0.00	0.06	0.94

the space of income values into fixed classes that are typically held constant over the study period. Estimates of the transition probability matrices for interval s are obtained by accumulating the empirical transitions over each s length interval within the larger study period and normalizing by the number of regions that begin a period within an income class.

The empirical transition probability matrix provides rich insights as to the evolution of the distribution over time. For example, strong convergence in regional incomes over time would be reflected in the distribution concentrating in the middle income classes. Conversely, divergence would result in a more multi-model, or twin-peaks (Quah, 1996b), distribution.

The transition probability matrix maps the income distribution from one period into the distribution for the next period:

$$P_{t+s} = P_t M_{t,t+s} \tag{2}$$

where P_t is a $1 \times k$ probability distribution vector that summarizes the distribution for period t. Table 1 reports the empirical transition matrix for the case of the US over the 1929-99 period. The estimates are based on annual transitions between five income classes, the upper bounds of which correspond to the quintiles of the relative (US=1.00) incomes in 1929.

There are a number of indices that can be calculated from the transition matrix that provide summaries of the amount of mobility in the distribution. Shorrock (1978) introduced the following index:

$$SI = \frac{k - Tr\left(M_{t,t+s}\right)}{k-1} \tag{3}$$

where Tr indicates the trace operator. Shorrock's index is bounded on the $[0, 1.25]$ with interval lower values reflecting less mobility across income classes over time. The value of this index for the annual transitions from table 1 is 0.141. While this is towards the low end of the mobility spectrum it is important to recall that the probabilities are estimated for annual transitions. Even at this interval, the relatively higher mobility rates for the first three classes work to have the final marginal distribution such that there are no states remaining in the first class, with 5, 11, 26 and 6, in classes 2-5. This is evidence of very strong upward convergence.

2.3 Internal Mixing

While Shorrock's measures of mobility obtained from a transition matrix provides one view of the evolution of regional income distributions it does not necessarily speak to the question of relative mobility. Indeed, mobility across income classes need not imply changes in the relative positions of economies in the distribution. By the same token, low measures of income mobility, as measured by the Shorrock's index, could also be associated with a high degree of positional flux.

There are several mobility measures that are sensitive to changes in the ordinal ranking of economies in the income distribution. Kendall's τ statistic considers the degree of concordance in the rankings of all pairs of observations for two variables. In the context of income mobility, the first variable would pertain to the regional incomes for the initial year, while the second would be the incomes in the end year of the interval period. If two regions have the same relative rankings in both periods that pair is said to be concordant. However, if the relative rankings of the two switch over the interval, then the pair is discordant. With n observations there are $(n^2 - n)/2$ pairwise comparisons to be made. Kendall's τ is given as:

$$\tau = \frac{N_c - N_d}{(n^2 - n)/2} \tag{4}$$

where N_c is the number of concordant pairs, and N_d the number of discordant pairs. If all pairs are concordant, then $N_c = (n^2 - n)/2$, $N_d = 0$ and $\tau = 1$, while if all pairs are discordant, then $\tau = -1$.

As a non-parametric test, τ is useful in cases where the normality assumption is tenuous. At the same time, however, when applied to spatially referenced bi-variate distributions, the independence assumption may also be violated. In this paper, the properties of τ in the presence of spatial autocorrelation are examined. Extensions of τ to take spatial dependence into account are also presented and evaluated.

3 Spatial Dimensions

It seems desirable to consider the different dimensions (morphology, mobility and mixing) of regional income distributions together when drawing inference about the nature of regional economic growth processes. Limiting attention to only one of these dimensions may result in misguided inferences and only a partial understanding of growth dynamics. For example, an income distribution that retains the same shape over long periods of time may actually mask a great deal of internal mixing as individual economies move up and down the income distribution. At the same time a high degree of internal mixing might also occur over periods where the morphology of the distribution changes dramatically.

While all these dimensions are clearly important, the methods that have been adopted thus far to study these issues essentially ignore the spatial characteristics of the data and the role that regional context may play in shaping economic growth. There are a number of reasons why the spatial dimension needs to be incorporated more fully in analyses of regional income distributions.

From a theoretical perspective, some extensions to the work on endogenous growth theory have explored the role of technology diffusion as a mechanism to actually generate convergence even in the presence of increasing returns to scale (Barro and Sala-i-Martin, 1995, Ch 8.). In these models, poor economies are late adopters of technology which has been previously developed in the wealthier economies. To the extent that adoption costs are lower than innovation costs, the impact of the adopted technology works over a much shorter time-span in the poor economies compared to the wealthier regions. In this case the late adopters should experience higher growth rates following adoption.

Curiously absent in these diffusion-based endogenous growth models is any discussion of how the diffusion process may operate over space. Essentially these models consider only the relative technology gap separating economies, and it is that distance that determines the relative growth rates. But if diffusion operates as a spatial process, as a very rich geographic literature suggests it does, then some interesting spatial dynamics may lie beneath the regional income patterns examined in the literature. Extending these diffusion-led endogenous growth models to incorporate spatial structure would appear to be a promising direction to pursue.

A related question is the extent to which there are spill-overs in the regional growth process, and what forces might be driving any spill-overs that exist. This question touches on the debate surrounding cooperative versus competitive regional growth. For example, it is not clear if the ascendency of a region of states, such as the southern US states (Crown and Wheat, 1995), is driven by competition or cooperation between the member states. Of course both forces could be operating simultaneously within a group of states. There is also the issue of scale and the possibility that the nature of growth processes within groups of states is different from that across groups of states. For example, it could be that regional growth is collaborative within a region of states (i.e., Florida, Georgia, South Carolina) but competitive when viewed from a wider perspective (i.e., the southern states versus the northeastern states).

Another possibility is that growth is competitive, but that the nature of that competition varies depending upon whether the states are members of the same region or different regions. States within a given region may see their neighboring states as more direct competitors and focus their economic development strategies accordingly but give less attention to the activities of more distant states. A related question is whether intraregional competition could work to strengthen the region's competitive posture vis-à-vis other regions. Put another way, are the benefits of competition bounded by some regional context?

All of these issues surround the notion of regional cohesion and the extent to which economic growth is articulated in a heterogenous fashion across space. In other words, when studying the question of regional economic convergence, does the relevant unit of analysis become an individual state or should the focus be on groups of states and how these different groups move against one another?

While these are theoretical motivations for focusing on space in convergence analysis, what is also needed are new empirical strategies that can shed light on these issues. The recent focus on intra-distributional mobility has yielded important insights on regional growth dynamics, however, the possibility that moves of individual economies in the income distribution may be dependent upon those of their regional neighbors has largely been overlooked.[2]

[2]The work on estimation of kernel densities (Quah, 1996a) and mixture models (Tsionas, 2000) to study regional income distributions has ignored the complications that spatial dependence may pose for these approaches.

4 Methods for Spatial Dependence in Distributional Dynamics

4.1 Regional Conditioning

In the initial application of Markov models to the question of regional convergence Quah (1993) was cognizant of the possibility for regional clustering of incomes. He suggested the notion of "regional conditioning" as a way to represent this phenomenon. This is implemented using two different income distributions for a given point in time. The first is the distribution of incomes standardized to the national average, or what is referred to as the nationally conditioned distribution. This is compared to the regionally conditioned income distribution in which each economy's per capita income is expressed relative to the average of the incomes for its regional neighbors, defined as first order contiguous. From these two observations a "transition" matrix can be constructed to summarize to the degree of correspondence between the positions of an observation in each conditional distribution:

$$M_{R,N} = \begin{pmatrix} m_{R1,N1} & \dots & m_{R1,Nk} \\ m_{R2,N1} & \dots & m_{R2,Nk} \\ \vdots & \vdots & \vdots \\ m_{Rk,NK} & \dots & m_{Rk,Nk} \end{pmatrix} \tag{5}$$

where $m_{R2,Nk}$ is the empirical proportion of economies that were in class 2 in the regionally (R) conditioned distribution that fell in the kth income class of the nationally (N) conditioned distribution. Quah suggested that if incomes were randomly distributed in space, the transition matrix from (5) would be largely diagonal. Intuitively, this is akin to randomly sampling for the neighbors of each economy and then constructing the regionally conditioned distribution. In other words, individual economies would occupy similar positions in the two different conditional distributions if geography did not matter.

Curiously, Quah (1993) did not extend this reasoning to develop a statistic to formalize these intuitive notions. This is the task that we take up here. First we consider the construction of a statistic that could be used to evaluate the extent to which the regional income distributions depart from spatial randomness. Next we consider the distributional properties of this statistic.

One way to proceed is to treat each of the standardized (relative) per capita income distributions as marginal distributions and consider whether their joint distribution departs from the independence assumption. Under the independence assumption, the expected joint probability that an economy is in class 2 of the regionally conditioned distribution and class 3 of the nationally conditioned distribution would be:

$$\hat{M}_{2,3} = \frac{n_{2,R}}{\sum_l^k n_{l,R}} \times \frac{n_{3,N}}{\sum_l^k n_{j,N}} \tag{6}$$

where $n_{2,R}$ ($n_{3,R}$) is the number of observations in class 2 (3) of the regionally (nationally) conditioned distribution.

The difficulty here is that the substantive hypothesis we are interested in would be reflected in the joint probability matrix being non-diagonal. A non-diagonal joint probability matrix (i.e., what our "transition matrix" is being viewed as) could very well be consistent with the hypothesis that the two relative incomes are independent variates, but it is not the only outcome which is consistent with this. Put another way, spatial clustering (non-diagonality of the transition matrix) may or may not be consistent with the variate independence assumption (in a joint distribution sense).

A more direct way to implement a test for spatial clustering would be to examine whether the joint probability matrix departs from diagonality:

$$\zeta = 1 - \sum_l^k M_{l,l} \tag{7}$$

where $M_{l,l} = n_{l,l}/n$, with $n_{l,l}$ being the number of observations that are simultaneously members of class l in both relative distributions. As $0 \leq \zeta \leq 1$, lower values point to spatial randomness, and higher values indicate clustering.[3]

This statistic is similar to those used to test for non-diagonality of error covariance matrices in seemingly unrelated regressions (Breusch and Pagan, 1980). Of course the distributional properties of the latter tests are likely to be different from those for a test of the diagonality of a joint probability matrix. We will revisit this issue in the empirical analysis later in the paper.

4.2 Spatial Decomposition of Mobility

Quantifying the amount of regional income mobility is clearly an important task, which has attracted much recent attention. In this section, two new measures are presented which attempt to provide a view of the extent to

[3]Recall that the transition matrix is row-standardized, so technically speaking it is not the same form as a joint probability matrix since the latter is typically doubly stochastic.

which spatial dependence does or does not play a role in the overall level of regional income mobility.

A measure that allows for the decomposition of distributional mobility to analyze the amount of spatial clustering can be obtained as follows. Let $\theta_{i,t}$ represent the rank of state i's per-capita income in year t. Then between any two periods, a scalar measure of spatial clustering of distributional transitions is:

$$\Theta_{t1-t0} = \frac{\sum_R |\sum_{i\in R} \theta_{i,t1} - \theta_{i,t0}|}{\sum_i |\theta_{i,t1} - \theta_{i,t0}|} \tag{8}$$

where R is one of a set of exhaustive and mutually exclusive groups of states.

The denominator of this measure is simply the sum of the absolute rank changes over the period. To the extent that movements in the income distribution are cohesive within regions this measure should be closer to 1. The extreme case would be all states from one region increasing their ranks at the expense of states belonging to another region. In this case growth could be said to be competitive across the regions, or inter-regionally competitive. With less cohesion, the measure approaches 0. This is because the absolute value of the sum of the intraregional rank changes should be smaller when the states in question are moving in different directions in the distribution. In this case growth is competitive irrespective of geography.

A second approach towards studying the role of spatial dependence in income mobility is to apply a spatially modified rank correlation statistic. This focuses more on the question of internal regional cohesion, or the extent to which relative positions in the income distribution remain fixed, or not fixed, depending upon whether two economies are regional neighbors. The concordant and discordant count measures from (4) can be further decomposed to consider which pairs involved observations from the same region and which considered observations from different regions. More specifically the number of concordant pairs can be decomposed into:

$$N_c = N_{c,r} + N_{c,o} \tag{9}$$

where $N_{c,r}$ is the number of concordant pairs involving locations belonging to the same region, and $N_{c,o}$ are the number of concordant pairs for observations belonging to different regions. A similar decomposition holds for the discordant pairs N_d. To develop a spatial version of the τ statistic from equation (4), define:

$$\omega = (n^2 - n)/2 \tag{10}$$

which is the denominator in the original form of the statistic. This is also equal to the number of elements above (or below) the main diagonal in the spatial weights matrix. Each element in that matrix specifies whether observations i and j are considered members of the same region (or more generally neighbors). The sum of these elements can also be decomposed:

$$\omega = \omega_r - \omega_o \tag{11}$$

where ω_r is the number of pairs of observations that are members of the same region. From this, a spatial version of the rank mobility measure is:[4]

$$\tau_r = \frac{N_{c,r} - N_{d,r}}{\omega_r} \tag{12}$$

A similar measure can be derived for the non-neighbor pairs of observations τ_o. The original measure of rank mobility can then be decomposed as follows:

$$\tau = \psi\tau_r + (1 - \psi)\tau_o \tag{13}$$

with $\psi = \omega_r/\omega$.

This decomposition opens up some interesting possibilities. For example, we can ask if the discordant counts are mainly due to changes in the rankings involving pairs of economies from different regions (i.e., interregional) or from within the same region (i.e., intraregional). Even when $\tau = 0$, in which case the number of concordant and discordant pairs are equal, this question still is an interesting one since it would shed light on the nature of regional cohesion.

The decomposition can also speak to the question of whether growth is competitive within regions as well as across regions. Interregional growth is characterized by one group of states moving ahead of another group in the distribution. The spatial decomposition would allow us to examine whether the relative positions between the states in a group moving up (or down) the distribution remain invariant to the movement of the group as a whole.

Rank correlation tests are non-parametric but still rest on the random sampling assumption. Consequently, when applied to georeferenced data, this assumption becomes questionable. As such, the tests are initially treated as indices of spatial dependence in distributional mobility and are applied in an exploratory mode. An initial investigation into the properties of these tests is also carried out using empirically generated sampling distributions based on Monte Carlo techniques.

[4] The spatial τ statistic presented here can be viewed as a dynamic extension of the rank adjacency statistic recently presented in Ekwaru and Walter (2001a,b). Future work will explore the relationships between these two statistics.

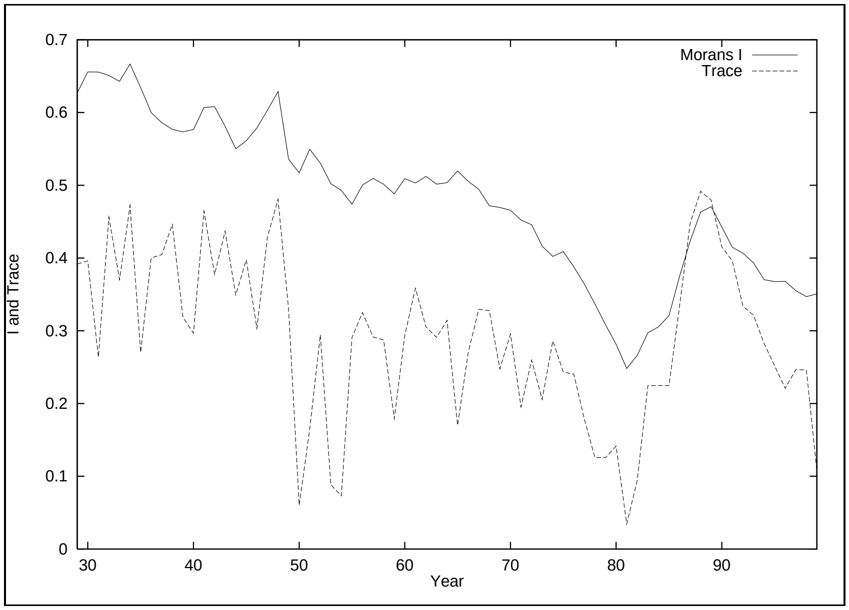

Figure 4: Spatial Autocorrelation of Per Capita Income Distributions 1929-99

5 Empirical Illustration

To provide some initial insight as to the properties of these new measures, a series of simulations was carried out using income data for the U.S. over the 1929-99 period.

5.1 Regional Conditioning

The first analysis focuses on the trace statistic ζ from (7) for measuring the degree of spatial autocorrelation in regional incomes in a given year. The results are presented in figure 4 which plots the trace statistic together with the value of Moran's I for each year in the sample. The trace statistic in figure 4 is implemented with five classes where the class boundaries are expressed in terms of incomes as a percentage of the national average. The relative incomes associated with the quintiles for the first year are used to define the cut-offs for the classes in the remaining years. The same row-standardized first order contiguity matrix is used to implement both the trace statistic and Moran's I.

The two statistics display similar behavior with respect to generally declining trends in the level of spatial clustering, although the trend is clearly more pronounced for Moran's I than for the trace statistic. Both tests also display sharp increases in value over the 1980's, followed by a resumption of the long term decline towards the end of the century. It is tempting to conclude that Moran's I displays more power relative to the trace statistic since it takes on a larger value for all except a few of the years. Because the two statistics have different scales, however, a direct comparison of their values as indicators of spatial clustering would be misleading. Instead, the relative strength of the signal each statistic yields regarding spatial autocorrelation needs to be viewed from an inferential perspective.

As a formal evaluation of the properties of the trace statistic have not yet been carried out, inference is based on 10,000 random permutations of the 48 incomes for each year in order to develop an empirical sampling distribution for the statistic. Pseudo p-values for the both the trace statistic and Moran's I are derived by considering the percentage of the simulated values that were more extreme than the value for the actual map of income values for that year. For each year of the study, the empirical value for Moran's I was significant at the 0.10, 0.05 and 0.01 levels, while the trace statistic was found to be significant in 68, 62 and 53 of the years, respectively. In all years the p-values are higher for the trace statistic compared to those for the Moran's I. Intuitively, because the trace statistic is based on an ordinal metric while Moran's I is based on a ratio metric, one could expect the former to display lower power against spatial dependence. This may account for the pattern displayed in figure 4, although a more detailed evaluation of this issue would require a formal analysis of the properties of the trace statistic.

5.2 Regional Cohesion of Rank Mobility

Figure 5 summarizes the results of applying the regional cohesion measure to the annual rank changes in state per capita incomes. The value of Θ from (8) for the realized income changes is plotted against the average value from 1,000 random permutations of the income changes for each year. In 56 of the 70 annual changes, the statistic takes on a value that is larger than the value that could be expected if the rank changes were randomly distributed in space. In 23 of the 70 cases the values are significantly different from their expected values, at the 0.05 level, while 12 and 27 values were significant at the 0.01 and 0.10 levels, respectively.

The value of Θ increases towards the end of the sample, while its expected value remains fairly constant over the entire period. Using 1968 as a split point confirms this as the average value of Θ before this year was 0.54,

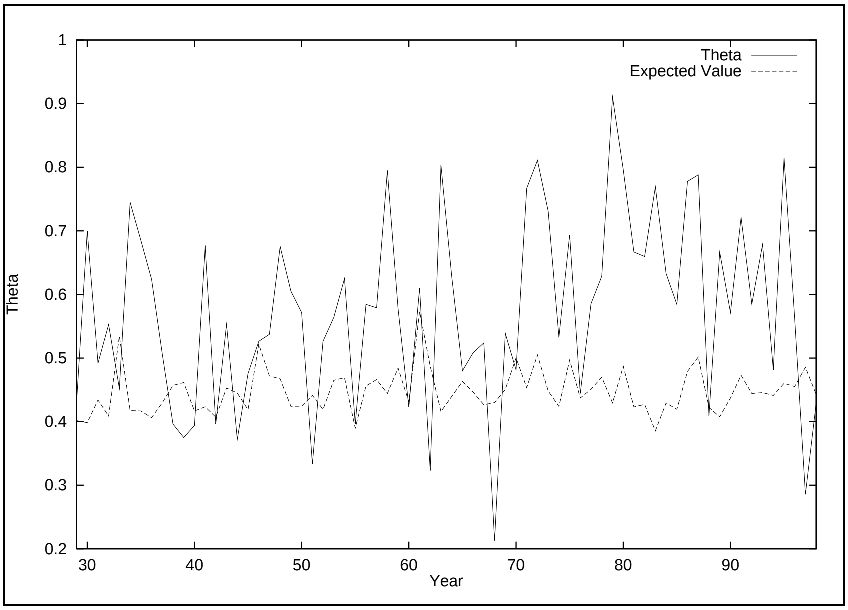

Figure 5: Spatial Cohesion Index: 1-year interval

but for the period following 1968 the average value was 0.63. The values obtained from the randomized maps averaged 0.445 before 1968 and 0.451 after the break.

These findings suggest that in over a third of the years external regional cohesion is present and that there has been a slight increase in the amount of such cohesion since 1968. An interesting possibility to consider is if this increase is related to the short run turn-around toward divergence over the the 1979-89 period. Elsewhere, Rey and Montouri (1999) have found that spatial autocorrelation in regional incomes has strengthened during periods of divergence during this century.

5.3 Spatial Decomposition of Rank Dynamics

Figures 6-9 display the traditional and spatial versions of the τ statistic for rank mobility over four different interval periods. Several findings emerge from a visual inspection of these figures. First, as expected, the amount of mobility tends to increase with the length of the interval under consideration.[5] The second regularity is that the mobility measure for the non-

[5]Higher values for τ reflect lower rates of mobility.

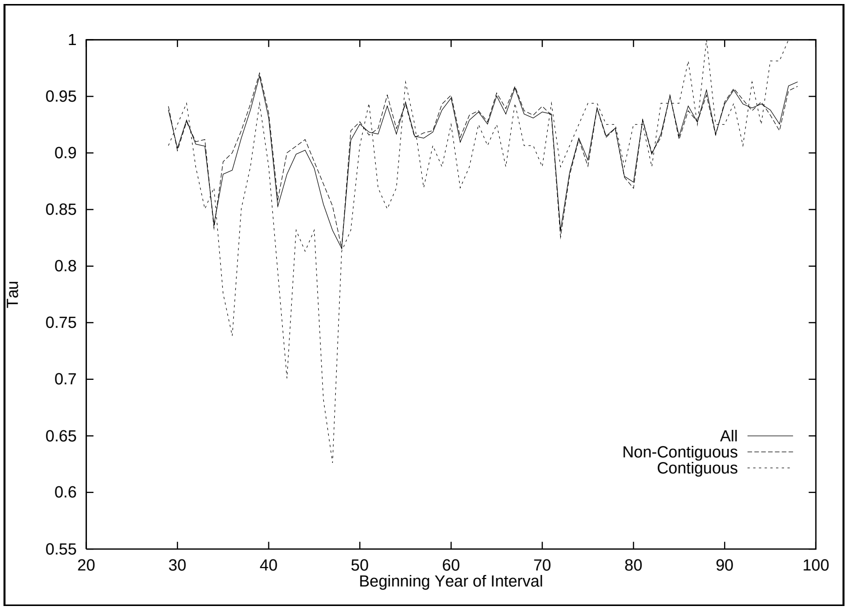

Figure 6: Spatial Rank Mobility Index: 1-year interval

contiguous pairs is much closer to that of the overall-pattern than is the case of mobility defined for contiguous pairs of states.

The main differences between the mobility rates for the contiguous and non-contiguous state are reflected in the generally higher rates for the contiguous pairs in the early part of the study, but lower mobility towards the end of the period. This is found for each of the four different interval lengths as well.

To test whether the differences in the rank mobility rates displayed in these series were significant, a randomization strategy was adopted. More specifically, 1,000 permutations were carried out, in each of which a state's time series was allocated to a potentially different location. For each permutation, the rank correlation statistics were calculated for all the different lengthed intervals. Values for these measures from the permutations were then used to develop an empirical sampling distribution against which the actual differences in mobility measures were compared. This allows for a consideration of the differences in the mobility measures for different length intervals as well as for specific years within these intervals.

Table 2 reports the specific intervals in which significant differences were found between the τ statistics from the neighboring and non-neighbor pairs.

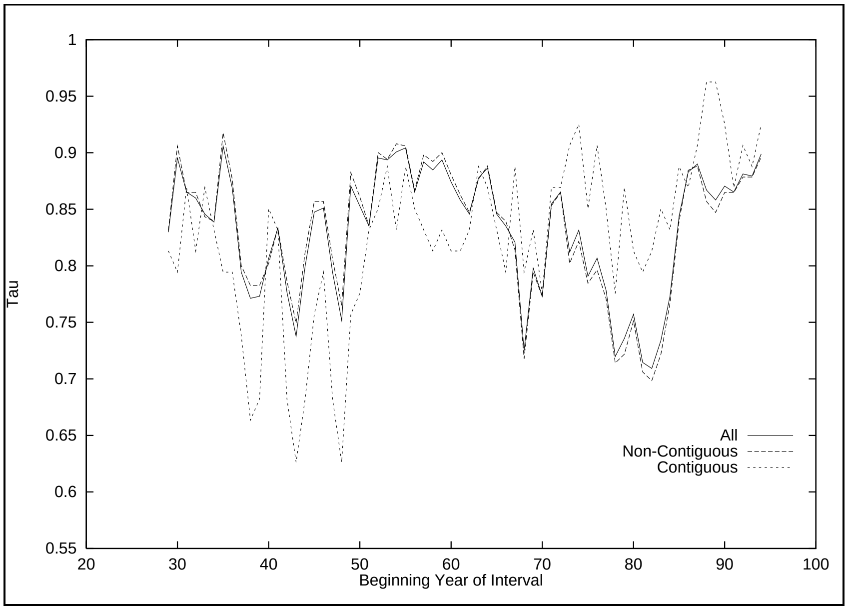

Figure 7: Spatial Rank Mobility Index: 5-year interval

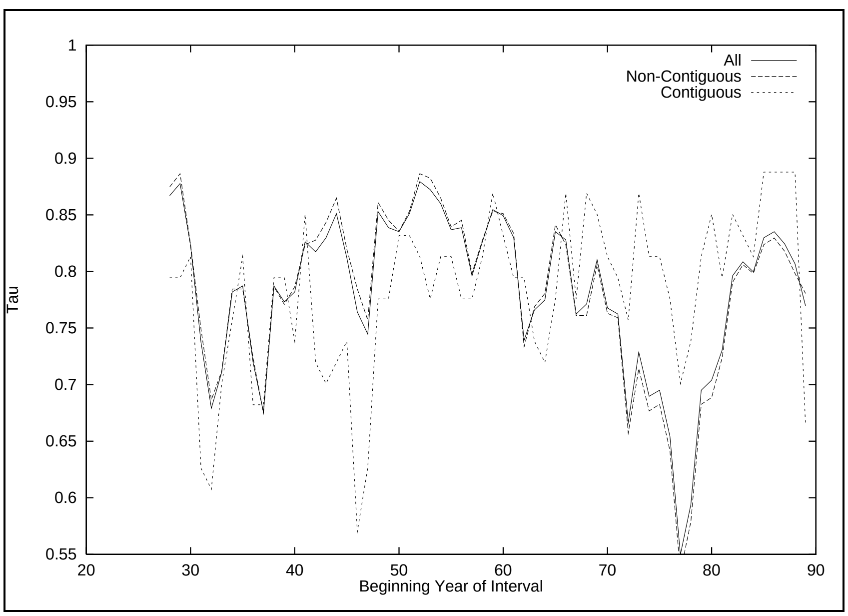

Figure 8: Spatial Rank Mobility Index: 10-year interval

Table 2: Differences in Regional Mobility

Start Year	Interval Length	$\tau_r - \tau_o$	Critical Value[a]
35	1	-0.117	0.097
36	1	-0.162	0.092
42	1	-0.199	0.093
44	1	-0.099	0.087
46	1	-0.190	0.100
47	1	-0.227	0.109
49	1	-0.088	0.084
53	1	-0.101	0.067
30	5	-0.112	0.090
35	5	-0.123	0.086
44	5	-0.130	0.118
47	5	-0.124	0.119
48	5	-0.139	0.130
49	5	-0.125	0.094
79	5	0.147	0.135
83	5	0.129	0.128
88	5	0.106	0.099
89	5	0.115	0.099
44	10	-0.142	0.105
45	10	-0.145	0.104
47	10	-0.214	0.123
54	10	-0.107	0.097
74	10	0.155	0.128
78	10	0.167	0.160
79	10	0.159	0.156
81	10	0.162	0.143
71	25	0.135	0.131
73	25	0.188	0.151
74	25	0.160	0.147

[a] 1.96 empirical standard deviations.

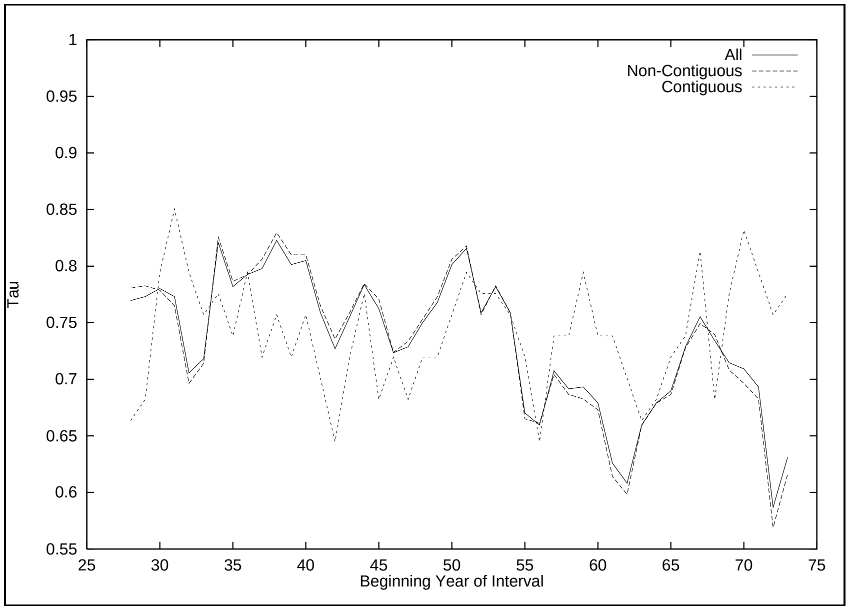

Figure 9: Spatial Rank Mobility Index: 25-year interval

Using plus or minus two standard deviations from the simulated rank differences for each interval, 29 of the 243 intervals generated significant differences in mobility between the groups. In eighteen of these intervals, rank mobility was greater within the set of neighboring pairs ($\tau_r < \tau_o$) than in the case of non-neighboring pairs of states. The majority of these cases were in the shorter (1 and 5-year intervals) and in the beginning of the study period (i.e., 1935-53).

The eleven intervals in which rank mobility was significantly weaker for the set of neighboring states versus the non-neighboring set tend to occur in the latter portion of the study period and involve longer lengthed intervals. These two patterns emerge during periods in which the rate and direction of convergence were different. One possible explanation for the higher mobility rates displayed by the contiguous pairs in the earlier years is that the overall levels of income dispersion were larger then, as was the level of spatial dependence. Consequently, the differences in incomes between neighboring pairs of states was likely to be smaller than income gaps separating non-contiguous states, and discordance in rank pairs was more likely for the former than latter group. In any event, the patterns suggest a possible relationship between the level of overall convergence and the strength of spatial autocorrelation in regional incomes.

6 Conclusion

This study has introduced three new measures for the study of spatial dependence in the context of regional income distributions and their dynamics. A trace statistic for spatial dependence was found to be in general agreement with the inferences based on the conventional Moran's I statistic. Because it is based on a ordinal metric the new test appears to possess somewhat less power than Moran's I, but a definitive conclusion on this awaits more detailed analysis of the test's formal properties.

Application of the two new measures of spatial clustering in rank mobility indicate that changes in ordinal positioning in the income distribution do not occur randomly in space. Interestingly, these statistics also appear to be sensitive to changes in the direction of the convergence path. This suggests that the relationship between spatial structure and regional income convergence may be worth further exploration in future studies.

While these new statistics show promise, much more work needs to be done on their theoretical properties and a number of implementation issues also need to be further investigated. Chief among these is the definition of the spatial weights matrix used to operationalize the mobility statistics and whether that matrix should be based on the notion of regional membership or more conventional distance and contiguity criteria.

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