

Spatial Clustering, Inequality and Income Convergence*

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Abstract

This paper examines the relationship between spatial clustering and inequality at the county scale with overall state per capita income in the U.S. over the period 1969-2000. For each of the 48 coterminous states we examine measures of inequality and spatial clustering and explore how a state's overall income level may be influenced by, or influence, these measures. Our exploratory analysis utilizes the open-source package Space-Time Analysis of Regional Systems (STARS) to illustrate some new techniques for analyzing regional income dynamics. The results provide insight into the possible relationships between inequality, clustering and relative income levels, and generates a number of interesting avenues for future research.

Key Words: spatial clustering; spatial dependence; inequality; convergence; geocomputation.

1 Introduction

The relationship between regional income inequality and regional growth has enjoyed a revival of interest since the early 1990's. A major reason for this is the rediscovery of the region as a meaningful observational unit for spatial economic analysis - a rediscovery reflected in the foundational

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papers by Krugman (1991) on economic geography and Barro and Sala-i-Martin (1991) on regional convergence. There has been much debate about the novelty of some of these ideas, as some scholars (Martin and Sunley, 1996; Isserman, 1996) point out that aspects of Krugman's arguments are similar to those made decades ago by Myrdal (1957) and Kaldor (1970) with an emphasis on increasing returns to scale and the resulting agglomeration of economic activity.

The debates about the lineage of recent regional economic theories mirrors a similar situation regarding the views of regional growth processes offered by the different schools of thought. For example, neoclassical theory posits that any initial regional disparities in incomes will tend to decline with regional growth in a market system through labor and capital mobility, subject to the regional economies sharing similar steady states. From this perspective, a negative relationship between regional inequality and growth is to be expected.

By contrast, the new economic geography school of thought (Fujita et al., 2001) stresses that regional growth tends to be spatially sticky in nature through cumulative causation processes that favor initially advantaged regions. Regional growth, in these models, is not expected to lead to a reduction of inequalities but rather increases. Similar predictions about a positive relationship between regional inequality and growth fall out of endogenous growth theories (Nijkamp and Poot, 1998) as well as the earlier theories of Kaldor and Myrdal.

Given the diversity of theoretical expectations regarding regional inequality and growth, it is not surprising that a growing number of empirical analyses of the question have appeared in recent years. However, the literature has tended to focus on the dynamics of regional inequality at the cost of largely overlooking the underlying geographic patterns of incomes. Put another way, the focus has been on changes in the statistical distribution of regional incomes and not on the spatial distribution of those incomes nor the relationship between the two distributions.

In this paper we suggest ways in which the geographic component of regional inequality analysis can be made more central. We empirically examine the relationship between spatial clustering, regional income inequality and growth in the United States over the period 1969-2000. We seek to expand the focus of the empirical literature on regional inequality and growth to include the role of spatial clustering as well as spatial scale. Our approach is to introduce some new exploratory techniques for regional inequality dynamics with the goal of generating fresh stylized facts on regional growth, clustering, and inequality.

The remainder of the paper is organized as follows. In the next section we motivate the specific issues we are interested in within the regional inequality literature. In section three we describe an exploratory analysis of spatial income inequality dynamics within the US. This section also contains an examination of the relationship between spatial inequality and spatial clustering in section four. The paper closes with a summary of key findings and a number of directions for future research.

2 Regional Inequality, Growth and Spatial Clustering

The relationship between inequality and economic growth has been examined in a number of contexts. The foundational paper by Kuznets (1955) provided a theoretical framework suggesting that the relationship between personal income inequality and economic development followed an inverted-U pattern. In early stages of economic development personal income inequality would be expected to be high as a prerequisite for the accumulation of capital to support industrial expansion. However, as development progresses personal income inequality would lessen due to higher wages and increased incomes being spread to other members of society.

The inverted-U hypothesis generated a number of early empirical studies that suggest economies with higher levels of income inequality tend to grow faster than those with more even personal income distributions. However, these findings have recently been called into question (Aghion et al., 1999). Moreover, the evidence on the direction of this relationship is rather mixed as a number of studies have examined the impacts of growth on inequality, as well the relationships between inequality, growth rates and investment (Barro, 2000).

Parallel to these studies at the international scale, literature examining the question of regional income inequality has also developed. This literature begins with the pioneering work by Williamson (1965) investigating the relationship between regional inequality and development. Williamson adapted Kuznet's inverted-U hypothesis to the regional case. In these studies, the focus is on how regional inequalities change as the level of development of the regional system (i.e., the collection of regions) proceeds. (Amos, 1988; Petrakos and Saratsis, 2000; Petrakos et al., 2003).

Closely related to the regional inverted-U theme is a second strand of the regional inequality literature that explored the geographic segmentation of inequality within regional systems. The general approach is to partition the

regional units into exhaustive and mutually exclusive groupings and then decompose the total inequality (across all regions) into that which is due to inequality internal to the partitions or inequality across the partitions. Representative studies of this approach include Fan and Casetti (1994); Nissan and Carter (1999); Fujita and Hu (2001); Azzoni (2001); Milanovic (2004); Rey (2004).

The regional inequality literature is distinct from that at the international scale in an important respect. Regional investigations have tended to view inequality as an outcome of growth processes. The question of whether inequality is good or bad for growth, which has commanded substantial attention in the international literature, has gone relatively unexamined at the regional scale where the causal arrow has implicitly been pointed from growth to inequality.

Although one would expect the role of space and the geographical distribution of incomes to be central to the regional inequality literature, this is not entirely the case. In the inequality-growth studies, regions only serve as observational units, with the focus on how the dispersion of incomes changes as the regional system evolves. As Arbia (2000) has pointed out, the measures of inequality used in these studies are insensitive to the underlying geographical distribution of the incomes. The decompositional studies do pay more attention to the territorial organization of the regional economies as is reflected in the various regionalization schemes used to operationalized the inequality decompositions. However, the spatial distribution of regional incomes within each of these partitions or the potential for interaction across these partitions have not been examined. As a result, the role of spatial clustering and spatial scale in regional inequality dynamics remains unknown.

While further refinements of regional theories are indeed needed, there is also much that can be done on the empirical front to push the literature forward. For example, previous work by (Amos, 1988) has shown that while the inverted-U hypothesis generally describes the relationship between levels of income and inequality between states in the U.S., the situation is much more mixed when examining that same relationship within the counties of individual states. This suggests a level of spatial heterogeneity in interregional inequality dynamics that needs to be incorporated into regional growth theory. We feel that by drawing on recent advances in exploratory space-time data analysis (ESTDA), it may be possible to uncover new empirical insights regarding the spatial dimensions of regional inequality dynamics. In particular, we are interested in the following set of question:

- What is the relationship between spatial clustering of regional incomes

and the growth of the system of regions?

- What is the relationship between changes in inequality between regional incomes and the level of spatial clustering of those incomes?
- Are the relationships between growth, inequality and spatial clustering robust to changes in spatial scale?

3 Exploratory Analysis of Income Dynamics Within US States

Our exploratory analysis of income dynamics in the US is divided into several parts. First, we examine the separate state level trends in income inequality and clustering from 1969–2000. These aggregate results are subsequently contrasted with those generated from county level data.¹ This allows us to consider whether the disparity and concentration of incomes is invariant to spatial scale. Furthermore, the disaggregated inequality and clustering results are examined in context with per capita income levels to determine whether a state’s relative performance is a factor in the processes. Next, internal inequality, spatial clustering and relative income levels are viewed in a pairwise manner across US states. This portion of the analysis uncovers the importance of examining both the correlations between variables and how they covary directionally over the time-span. Lastly, we look at whether inequality is spatially clustered among US states.

3.1 Explanation of Descriptive Statistics

To examine the disparity of incomes in the US we incorporate Theil’s T as a common global measure of inequality between regions:

$$T_t = \sum_{i=1}^n s_{i,t} [\log s_{i,t} - \log (1/n)], \quad (1)$$

¹The income data was collected from the Bureau of Economic Analysis (BEA). Several states experienced changes in the number of counties during our period of study. In 1982, Yuma AZ was divided into two counties: La Paz and Yuma. Cibola NM was created in 1981 from what used to be the western portion of Valencia county. While Menominee WS was born out of Shawano County in 1961, the BEA gathered data for both counties together until 1989. In all of these cases the data was backcasted based on proportions in the year of the corresponding split. Virginia contains a number of townships which were aggregated according to the BEA data. Contiguity for island counties were based on interstates (bridges) and ferry routes.

where $s_{i,t}$ signifies the share of income in time t for region i in a set of n region. While inequality points to an uneven distribution of wealth within a system, it fails to pinpoint how the regions are distributed in space. In order to explore the possibility of the way the incomes are distributed in space. In order to examine the spatial clustering of incomes we employed Moran's I as a measure of spatial autocorrelation²:

$$I_t = \frac{n}{S_0} \sum_i \sum_j \frac{w_{i,j}(x_{i,t} - \bar{x}_t)(x_{j,t} - \bar{x}_t)}{(x_{i,t} - \bar{x}_t)^2}, \quad (2)$$

where $x_{i,t}$ = **pcr** for region i in time t and S_0 = sum of all the elements in the spatial weights matrix. It is important to note that both Theil's T and Moran's I are sensitive to the number of observations. In order to make comparisons between individual state values, Theil's T was normalized by dividing by each states' value $T_{i,t}$ by its corresponding number of counties (n_i), and each Moran's $I_{i,t}$ value underwent a z -transformation.

3.2 Trends in Inequality and Clustering Across and Within US States

We begin our analysis by comparing the individual changes in income inequality and clustering in US states over several decades. In order to uncover possible scale effects we first view inequality and spatial co-location using the states as the unit of measure, and compare with results obtained using county level data.³ Figure 1 contains the global T (**theilT_US**) and z (**globalZ_US**) values for the US from 1969–2000 using each states' income as the unit of measure. The T -values decreased sharply in the early 1970s, but rebounded through the 1980s, only experience a subsequent decrease and increase in the 1990s. This points to an amount of temporal instability in the levels of income inequality in the US. The degree of spatial income concentrations also appears to fluctuate over the time period, however, the z -values for the aggregate US are significantly positive for all the time periods indicating the presence of spatial clustering of income among US states. Graphically, Figure 1 illustrates some similarities in the dynamics of the two series, suggesting a potential relationship between clustering and inequality over time.

²We incorporated normality as our basis of inference.

³All computation and visualization for this research was conducted in the Space-Time Analysis of Regional Systems (STARS) environment (Rey and Janikas, 2004). The STARS package can be downloaded at <http://stars-py.sourceforge.net/>

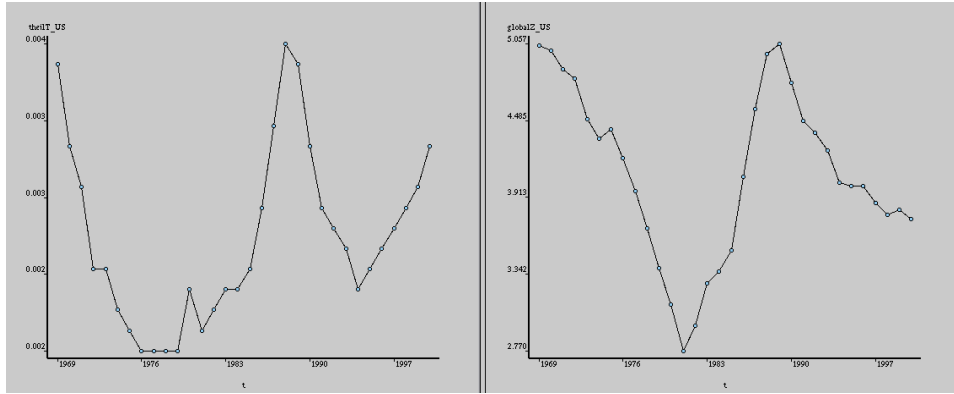


Figure 1: Global Theil's T and Moran's z values for the 48 Contiguous US States

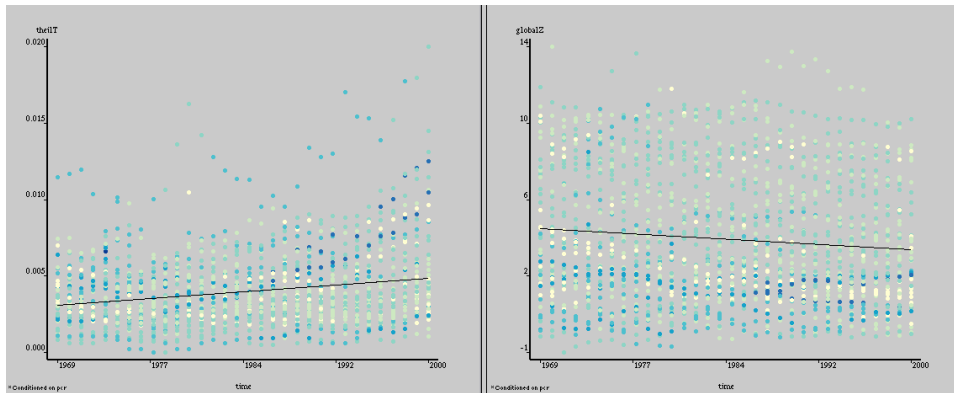


Figure 2: State Specific Inequality and Clustering Time Series Conditioned on Per Capita Income Relative to the US Average

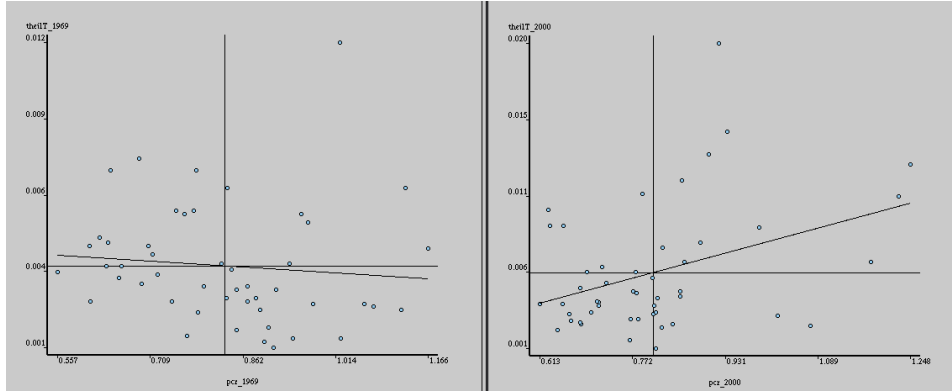


Figure 3: Internal Inequality and **pcr** for the Contiguous US States in 1969 and 2000

Next, we were interested in whether the levels of income inequality and clustering *within* US states displayed similar patterns as the aggregate US. Global T and z measures for each contiguous US state were constructed using counties as the internal unit of observation. This generated $n = 48$ values for each time period ($t = 32$) for both inequality (**theilT**) and clustering (**globalZ**). Figure 2 plots the results against time in order to display each states inequality and clustering series. Each data point is conditioned in color on the states' per capita income relative (**pcr**) to the national average during that time period.

The trend line for the T -values indicates a gentle increase in the level of income inequality within US states over the time period which stands in contrast to the unstable process at the US level. Most of the US states appear to have relatively stable internal levels in inequality. There is an increase at the end of the time-period which seems to correspond with the aggregate US state experience. Conditioning the values on **pcr** did not clearly distinguish any trend between inequality and a per capita income, however, when we plotted **pcr** against Theil's T for 1969 and 2000 separately as shown in Figure 3 we found that inequality was initially largest in states with low **pcr** and the process reversed during the course of study. This result suggests that inequality seems to be increasing in states with higher incomes.

While inequality within states has increased over time, Figure 2 displays a negative slope for the internal state z -values. This indicates a decrease in the level of spatial clustering within US states over the series, however, it is

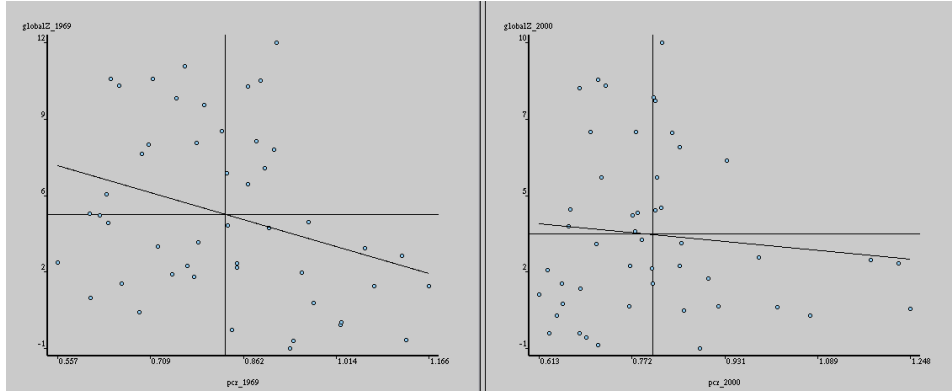


Figure 4: Internal Income Clustering and **pcr** for the Contiguous US States in 1969 and 2000

important to note that a majority of states remain significantly clustered.⁴ Similar to the scale differences for inequality, the internal state clustering patterns seem to be less volatile than the aggregate counterpart. Again, it was difficult to distinguish whether conditioning the series on per capita income demonstrated any systematic relationship. Similar to the inequality analysis, we plotted the z -values against **pcr** for 1969 and 2000 in Figure 4. The results illustrate a weakening in the possible relationship between relative incomes and the degree of spatial income concentration.

Our analysis of inequality and spatial clustering within US states has up to this point viewed each phenomenon independently of the other, either as a function of time or measured against relative income. The following sections explore the possible pairwise relationships between inequality, spatial clustering and economic growth.

3.3 Inequality, Clustering and Relative Income

An initial look at the global T and z value time series plots (Figure 1) hints at a possible relationship between state level income inequality and clustering as both series seem to follow a similar path. We were interested in whether this result held when the counties were used to calculate state values independently.

We used the conditional scatter plot to visualize spatial clustering and inequality subject to **pcr**. Figure 5 displays the results and highlights the

⁴35 out of 48 states have z -values above 2.6 in 2000.

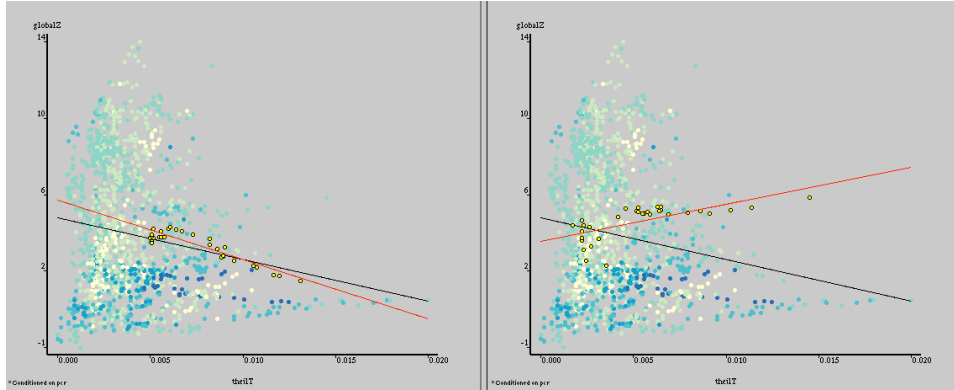


Figure 5: State Specific Income Clustering and Inequality Time Series Conditioned on Per Capita Income Relative to the US Average: Focus on New York (left) and California (right)

paths for New York and California. Overall, there appears to be a negative relationship between the disproportion and spatial concentration of incomes within US states, however, these results are not entirely indicative of each state's individual experience. For example, the focus on New York (left) seems consistent with the overall state trend while California (right) demonstrated a positive correlation between inequality and clustering. These results can be misleading in that they represent the correlation between income clustering and inequality but do not indicate whether inequality and clustering are both strengthening or weakening over time. In order to uncover the directional trend for New York and California we constructed separate time path plots which are displayed in Figure 6. Here each point represents the the z and T values for the state in question for every time period. Interestingly, we see that both states are increasing in inequality over the time period, but are displaying opposite trends in spatial clustering. This results indicates the importance of both identifying the degree of correlation between the variables but also their corresponding directional co-movement over time.

3.4 Pairwise Variable Correlation and Directional Analysis

We wanted to distinguish both the type and magnitude of the correlation between relative incomes, spatial clustering and inequality, as well as their time-wise directional similarities. We first created correlation coefficients for

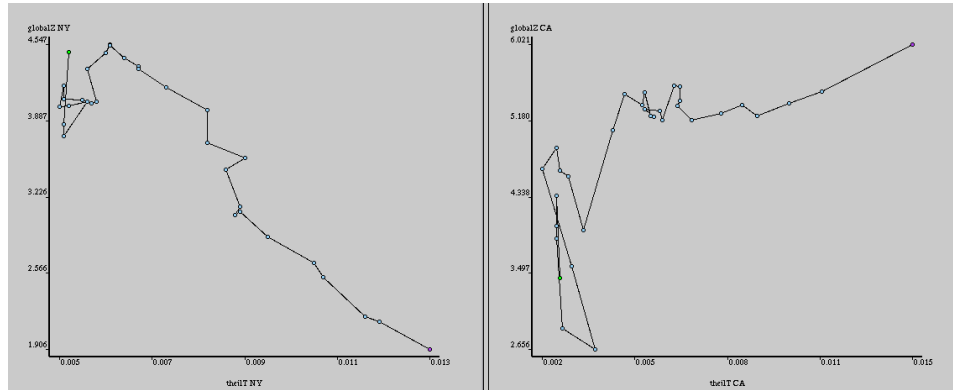


Figure 6: State Income Clustering and Inequality Time Paths for New York and California

each combination in the set of three variables:

1. Corr[**pcr**, Theil's T]
2. Corr[**pcr**, Moran's z -values]
3. Corr[Moran's z -values, Theil's T].

These values were constructed for each state based on their county values over the time period. In order to summarize the directional change of a state's internal income dynamics we calculated the correlation between each variable and time. A state could experience one of four possible outcomes for each pair of variables:

1. ++ = Variables 1 and 2 both increasing.
2. -+ = Variable 1 decreasing while Variable 2 increasing.
3. -- = Variable 1 and 2 both decreasing.
4. +- = Variable 1 increasing while Variable 2 decreasing.

Table 1 contains results for this analysis. The first column contains the pairwise directional change values for relative income and inequality. For example: California had a value of -+ which indicates that relative income was decreasing within the state over the time period while inequality was increasing. Figure 7 contains two maps, the first of which contains each

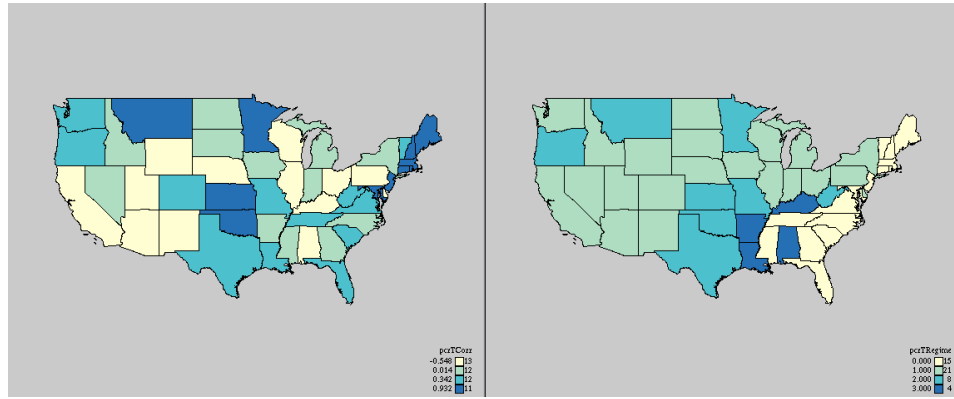


Figure 7: State Income and Inequality Correlations and Corresponding Time Trend Regimes

state’s correlation coefficient between relative income and inequality, while the second displays the directional results from column one in Table 1.⁵

By mapping the results it became apparent that there is an amount of regional cohesion in the dynamics. Much of the South and Northeast are experiencing increases in internal inequality and income relative to the national average. The Rust-Belt states and much of the West are decreasing in relative income as internal inequality increases. The correlation map (left) in Figure 7 reports a strong positive linear association between inequality and the level relative income in the Northeast states of Maine, New Hampshire, Massachusetts and Connecticut. Coupling this result with the ++ value displayed in the directional trend map (right) indicates that inequality and relative incomes increased over time in these states. This an important result because states such as Montana, Oklahoma and Kansas also had strong positive correlations but had – values on the directional map, indicating that both inequality and relative income levels were decreasing within their economies.

Table 1: Summary Table for Time-Trend Regimes

State	Income and Inequality	Income and Clustering	Clustering and Inequality
AL	+-	+-	-

continued on next page

⁵We use scatter-plot quadrants to distinguish the four possible types of trends: ++ = 0, -+ = 1, -- = 2, +- = 3.

Table 1: Continued

State	Income and Inequality	Income and Clustering	Clustering and Inequality
AZ	-+	-	-+
AR	+-	+-	-
CA	-+	-+	++
CO	-+	-	-+
CT	++	+-	-+
DE	-+	-+	++
FL	++	+-	-+
GA	++	+-	-+
ID	-+	-	-+
IL	-+	-	-+
IN	-+	-	-+
IA	-+	-	-+
KS	-	-	-
KY	+-	+-	-
LA	+-	+-	-
ME	++	+-	-+
MD	++	+-	-+
MA	++	++	++
MI	-+	-	-+
MN	-	-	-
MS	++	+-	-+
MO	-	-	-
MT	-	-	-
NE	-+	-	-+
NV	-+	-+	++
NH	++	++	++
NJ	++	+-	-+
NM	-+	-+	++
NY	-+	-	-+
NC	++	+-	-+
ND	-+	-+	++
OH	-+	-	-+
OK	-	-	-
OR	-	-+	+-
PA	-+	-	-+
RI	++	++	++
SC	++	+-	-+

continued on next page

Table 1: Continued

State	Income and Inequality	Income and Clustering	Clustering and Inequality
SD	-+	-+	++
TN	++	+-	-+
TX	-	-+	+-
UT	-+	-	-+
VT	++	+-	-+
VA	++	++	++
WA	-+	-+	++
WV	-	-	-
WI	-+	-	-+
WY	-+	-	-+
% in ++	31.25	8.33	22.92
% in -+	43.75	18.75	52.08
% in -	16.67	41.67	20.83
% in +-	8.33	31.25	4.17

The most common type of dynamics for US states was a decrease in relative income and an increase in inequality (% -+ = 43.75). This opposite pairing is countered however, by the large number of states with positive correlations between inequality and relative incomes (% ++ = 31.25, % - = 16.67). Only four states (Alabama, Arkansas, Kentucky, and Louisiana) had positive increases in relative income and decreases in inequality.

The second column of Table 1 contains the directional pairings for the measures of relative income and spatial clustering. Similar to the results in the previous analysis there appears to be some regional similarities as distinguishable patterns exist on the maps in Figure 8. The South experienced an increase in relative income while the level of spatial clustering decreased. The Industrial Mid-West appeared to decrease in both relative income and spatial clustering.

We can again make use of pairing the two maps to provide a more detailed view of a states' experience over the time period. A closer look at New Mexico provides a clear example. The variable to variable correlation map reports that there was a negative relationship between relative income and clustering within the state, but gives no indication as to which variable was increasing and which was decreasing. The directional trend map indicates that New Mexico was in column 2 in Table 1 which signifies the state experienced a decrease in relative income while clustering within the state increased.

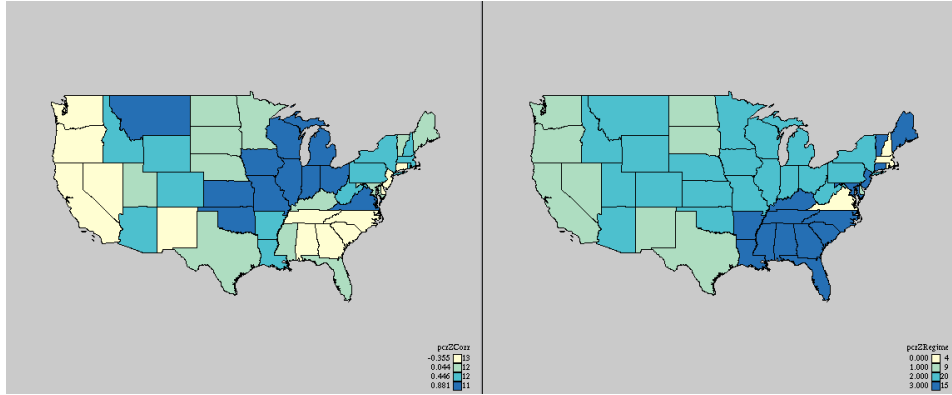


Figure 8: State Income and Clustering Correlations and Corresponding Time Trend Regimes

Shifting attention to the bottom of column two in Table 1 we find that the most common pairing of directional movements for relative incomes and clustering was $-$ at 41.67%. This indicates that the majority of states are experiencing decreases in relative income and spatial clustering. The second most common pairing of trends among US states is the $+ -$ category, indicating that income is increasing while spatial clustering is decreasing. Overall, roughly 72% of states have negative trends in spatial clustering.

The last column in Table 1 pairs up the clustering and inequality measures to see how they covaried over time (see Figure 9 for visual comparisons). There was still a slight indication of regional similarity, particularly among the Rust-Belt states which experienced increases in inequality and decreases in spatial clustering. The correlation map in Figure 9 indicates that roughly half the states had negative correlations between inequality and spatial clustering. Using this information in conjunction with the directional trend map we can identify states such as California and New Mexico that had a strong correlation between clustering and inequality which both increased over time. Conversely, Alabama, Arkansas, and Louisiana also had a strong positive relationship but the trend indicates these states decreased in levels of clustering and inequality from 1969–2000.

Over half the US states displayed negative spatial clustering trends and increases in inequality ($\% - + = 52.08$). The remaining half seem to exhibit either $++$ or $-$ patterns. Only two states had a positive slope for clustering and a negative one for inequality (Oregon and Texas). The experience for

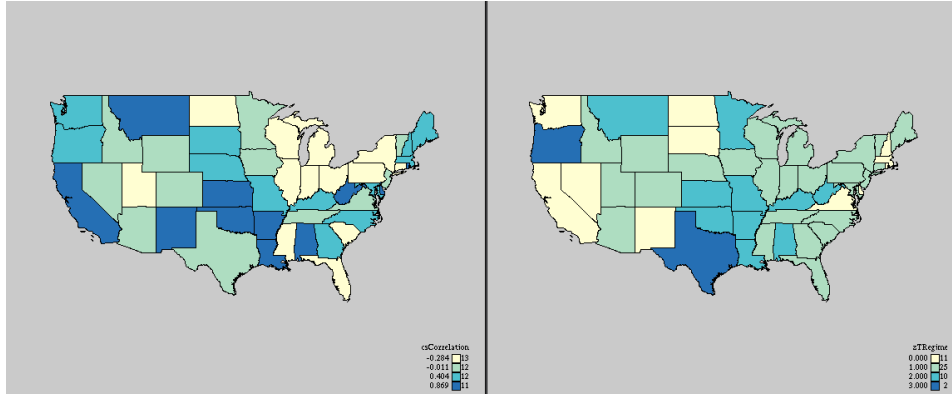


Figure 9: State Clustering and Inequality Correlations and Corresponding Time Trend Regimes

these two states are not identical however, as Texas had a negative correlation coefficient ($-.238$) but Oregon did not ($.259$).

3.5 The Spatial Clustering of Internal State Inequality

Next we considered whether intrastate income inequality was in itself spatially clustered, i.e. are states with high levels of internal inequality located next to states with similar levels of inequality? To get at this question we used internal state Theil's T values as the variable in equation 2. We then plotted the Moran's z -values for spatial autocorrelation based on each states inequality statistic. Figure 10 shows the time series for Moran's I for intrastate inequality (left) and a conditional scatter plot (right), where the relationship between inequality and the spatial lag of inequality is conditioned on the level of income (**pcr**). The spatial distribution of intrastate inequality is spatially autocorrelated in most years, with the exceptions being 1970, 1978, 1980 and 1988. In other words, states with high (low) levels of internal inequality tend to be located next to other states with high (low) levels of inequality. From a dynamic perspective, the conditional scatter plot reveals that the spatial clustering tends to be more stable for states with lower incomes as the lighter values tend to be more centered in the plot and the darker values appear more dispersed.

Figure 11 gives an indication of the degree of inequality clustering in 1969 and 2000. The first thing to notice is that there is an increase in the amount of inequality clustering. This is evident in the sharp incline in

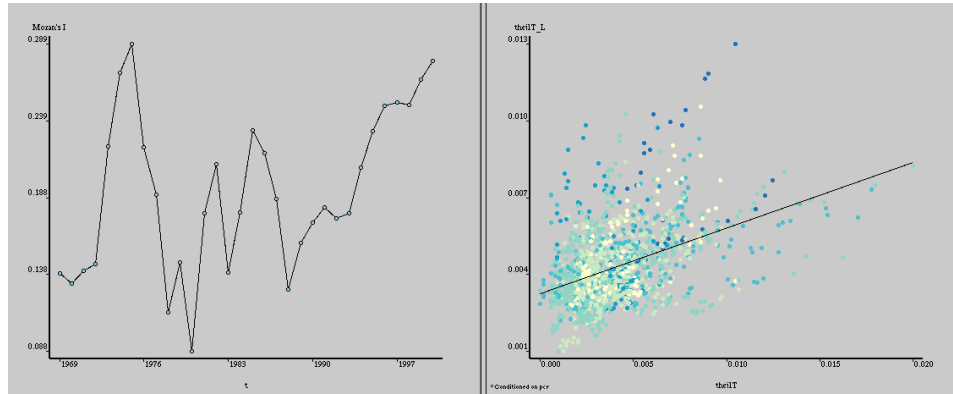


Figure 10: Moran's I for Inequality in the US and the Spatial Clustering of Internal State Inequality Levels Conditioned on **pcr**

the time-series plot and the steeper slope in the 2000 Moran scatter-plot as opposed to the corresponding scatter-plot for 1969. Another interesting thing to take note of is that there appears to be some mobility in this process. States with high values of internal clustering that neighbor other states with high inequality (quadrant 1) were highlighted in Figure (11). States such as Texas and Florida were in quadrant 1 in 1969 but are no longer present in 2000. Conversely, California and New York are among the states that were not in quadrant 1 in 1969 but transitioned to it by 2000.

4 Conclusions

There has been a resurgent interest in the ties between the regional disparities of income and economic growth over the last decade. The approaches dedicated to examining these relationships vary in theory and application. Furthermore, the regional aspect of these analyses places additional importance on the spatial structure of the processes. While the literature on economic growth has enjoyed ample progress in the incorporation of spatially explicit methods, the treatment of space within the context of regional inequality has been relatively ignored. Our paper focused on exploring the possible spatial characteristics of regional inequality and economic growth processes within the U.S..

Our analysis on the relationship between inequality and changes in relative income uncovered several interesting results. First, we found that

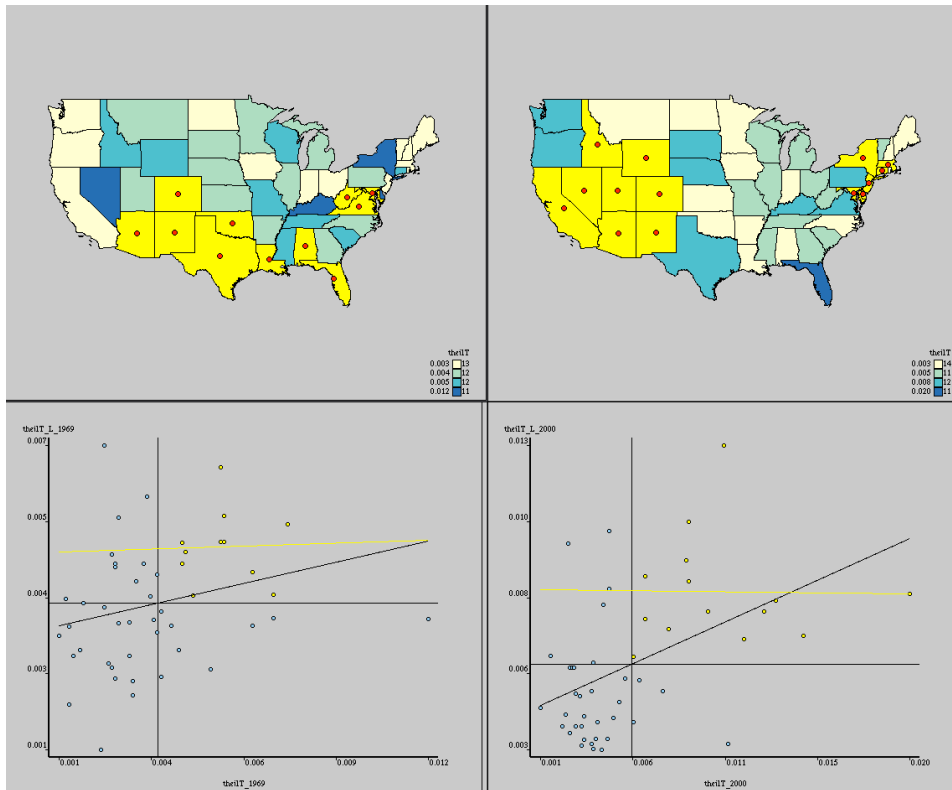


Figure 11: Spatial Clustering of Internal State Inequality Levels in 1969 and 2000

changes in inequality for the US as a whole is not indicative of what occurs internally in state economies. Through disaggregation we found that inequality within US states has increased from 1969 to 2000. Furthermore, we noted that there has been a positive movement in the relationship between inequality and relative income levels. There also appeared to be a degree of regional cohesion as the mapped results identified neighboring states with similar internal changes in inequality and relative income levels.

We then focused on the relationships between relative incomes and spatial clustering. Again, we found that examining clustering across US states can mask important internal socio-economic dynamics and therefore, does not necessarily represent what occurs within state economies. We found that clustering within US states has decreased over the time period. This needs to be taken into perspective however, as a large number of US states remain significantly clustered. It was noted that there was a negative relationship between the internal level of spatial clustering and the relative income of the state economy, but the correlation appeared to weakened over time. Similar to the inequality and income analysis, there seemed to be a element of regional cohesion in the process as neighboring states tended to display similar dynamics.

Shifting our attention to the relationship between inequality and clustering, we found substantial differences when examined across US states as opposed to what was occurring internally. At the aggregate US level, there is a strong positive relationship between inequality and clustering. This stands in stark contrast to the results for internal state economies where it appears the general relationship is negative. The ties between inequality and clustering appears to be more volatile than their respective comparisons with relative incomes. The correlation between clustering and inequality can be very different for states with similar levels of relative income. This is perhaps manifested in the less evident formation of similar regional groupings.

We noted the importance of examining both the type and magnitude of the correlations between relative incomes, inequality and clustering, as well as the direction of change over time. By comparing the directional change in each pair of variables with their corresponding correlations we were able to identify unique dynamic paths for each state economy. By contrasting the mapped results we also uncovered a degree of regional cohesion among US states in several of the processes. We found evidence that inequality across US states is spatially clustered. Furthermore, the degree of positive spatial dependence for inequality appears to be increasing. Lastly, the spatial clustering of inequality seems to be more volatile in states with higher relative incomes and there is evidence to the presence of state mobility in

the process.

Our exploration of space within regional inequality and growth dynamics has uncovered several important paths for future research. From a confirmatory perspective, it would be fruitful to examine whether inequality is a structural driver in the economic growth of a region. This could be addressed by including a measure of regional inequality as a regressor in a spatial econometric growth model. It would be interesting to allow for heterogeneity in this coefficient to test for regime structures in the process. If present, these groupings could be used to extend our exploratory analysis. It would also be beneficial to add a joint count analysis to test whether there are spatial regime structures in the pairwise directional movement and correlation of inequality, clustering and relative incomes among US states. Lastly, our understanding of the dynamic aspects of regional income inequality could perhaps benefit from the incorporation recent advances in spatial Markov Chain modeling.

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