DOES THE BUSINESS CYCLE MATTER FOR CONVERGENCE TESTING? EVIDENCE FROM U.S. COMMUTING ZONE LEVEL DATA, 1973-2007

BY

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THESIS

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Abstract

This research investigated regional growth patterns under different economic environments. Based on the varying innovation capacities that occur at different stages of the business cycle, I hypothesize that in the more advanced stages of regional development, regional income inequality increases during a normal growth period and decreases during a recession-recovery period. I tested this hypothesis with U.S. per capita income data from 1973 to 2007. This study found evidence supporting the hypothesis: under normal growth periods, regional convergence rate is lower; while during recession-recovery periods, regional convergence rate is higher. This study also found that the overall trend of the convergence rate was decreasing.

Key Words: convergence, divergence, normal growth period, recession-recovery period, business /innovation cycle, spatial spillover

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1. Introduction

This study looks at regional inequality and regional convergence through a different perspective, and it offers a new explanation for the current regional development trends in the United States. From the regional inequality literatures, many empirical studies find that there has been increasing regional inequality since the 1970s (Amos, 1988; Fan & Casetti, 1994). On the other hand, the regional convergence literature also finds that the convergence rate among US states has been slowing down since the 1940s (Carlino & Mills, 1996; Rey & Montouri, 1999). Both regional inequality and regional convergence literatures are finding evidence to support the claim that regional differences increase during the latter stages of economic development of a nation. The evidence from the regional literature is similar to that found in social inequality research, where it was noted that labor income inequality increased after the 1970s (Harrison & Bluestone, 1990; Levy & Murnane, 1992). However, is the increase in regional inequality really a "new trend" in regional development? Or could it be that the results presented in the papers by Amos (1988) and Fan & Casetti (1994) was merely a temporal fluctuation? The present research will attempt to answer the question from the perspective of economic cycles.

In the latter stages of economic development of a nation, when sub-national/regional (hereafter, "regional" will be used instead of "sub-national") inequality moves from significant disparities to greater equality, the regional inequality level will not always stabilize – it could continue to increase and decrease over time, sometime drastically. Drawing on Schumpeter's (1939, 1947) business cycle and evolutionary economics theories, entrepreneurs are seen as the main cause of economic development. The innovations from entrepreneurs disturb the economic equilibrium and push the economic and technological frontiers in cyclic waves. Connecting Schumpeter's evolutionary economics theory with Vernon's product cycle concept (Vernon, 1966), innovation occurs in certain regions, and the economic benefit of the new invention will spread to all the other regions. Schumpeter's theories explain the creation of business cycles by innovation along the temporal scale, while Vernon's product cycle concept explains the expansion of innovation for the spatial scale. Therefore, inter-regional growth over time can also be connected with innovation and business cycle.

This paper will present a regional growth theory based on the Schumpeter business cycle and innovation theories. This will be used to re-examine the regional inequality and regional convergence debates.

The paper is organized as follows. Section 2 outlines the competing theories of regional growth and development. Building on these competing regional growth theories, section 2 also illustrates the hypothesis used in this study. Section 3 provides an exploratory analysis about U.S. regional per capital income growth. In this section, I classify six sub-periods as my study objective and use some spatial statistic tools to understand the temporal and spatial changes that occur in U.S. regional income. Section 4 presents a conventional convergence model and a spatial convergence model that takes spatial externalities into consideration. Section 5 provides three sets of econometric analysis--OLS, spatial regression, and quantile regression--to explore and implement an absolute β-convergence model. Section 6 provides some discussion and conclusions.

2. Literature review and research hypothesis

The debate over regional growth theories led to many empirical papers that examined the change of regional inequality and regional income convergence/divergence. This chapter focuses on the theoretical regional growth literature. There are two traditional streams of regional growth theories. On one side, there is neo-classical growth theory that believes poorer regions will grow faster than richer regions (Solow, 1956). On the other side, there is the cumulated causation/ polarization growth theory (Myrdal, 1957; Hirschman, 1958) that believes richer regions grow faster than poorer regions. Towards the end of 1980s, the endogenous growth theory (Romer, 1986; Lucas, 1988; Aghion & Howitt, 1990) introduced the concept of increase returns to scale to the neo-classical growth theory. The endogenous growth theory also believes that richer regions grow at faster rates. Therefore, convergence has been considered to be an implication of new-classical growth theory, while the cumulated causation and endogenous growth theories did not have this same implication.

Differing from the existing regional growth literature, this paper suggests a regional growth pattern in which the forces of convergence and divergence exist simultaneously. Based on the Schumpeter theory of the business cycle and innovation and the Vernon product cycle concept, this paper argues that the forces of divergence are stronger in a normal growth period than in a recession-recovery period. Thus, the forces of divergence change over time, while the forces of convergence are relatively more stable. This paper assumes that the regional inequality level could increases during normal growth period because the forces of divergence are stronger.

The neo-classical growth theory

Neo-classical growth theory is based on the Harrod-Domar growth model (Harrod, 1939; Domar, 1946). The model assumes that the economic growth rate depends on the level of saving, the capital-output ratio, and the population growth rate. According to this model, regions with capital intensive production technology grow slower than regions with production technology that is less capital intensive, *ceteris paribus*. Thus, given the same saving rate and population growth rate, capital less intensive regions could grow faster than capital intensive regions. The limitation of the Harrod-Domar model is that the savings rate, population growth rate and capital-output ratio are assumed to be exogenous. However, in reality, all these three variables can be endogenously determined by the income level.

The Solow model (1956) improves upon the Harrod-Domar model by including the capital-output ratio as an endogenous variable. The key assumption in the Solow model is that there are diminishing returns to labor and capital. This means that, given a fixed stock of labor, another unit of capital will have less impact on output than the unit of capital that comes before. The same rule applies to adding one more unit of labor. Therefore, in the process of economic advancement (or development), the growth rate will decrease as capital stock increases. Hence, according to the Solow model, an economy will converge to a steady state rate of growth. The steady state rate of growth means that the growth rate depends on both the technological progress and the labor force growth rate.

The Solow model predicts convergence—that poorer countries or regions tend to catch up with richer countries/regions in terms of per capita income level. The strongest prediction is the unconditional convergence—that all countries/regions starting with different per capita income levels will converge to the same level of income. From the statistical perspective, convergence means that, for example, regional per capita income levels and regional per capita income growth rates have a negative relationship (Barro & Sala-i-Martin, 1992).

Cumulative causation/polarization growth theory

On the other side of the growth theory debate is the Cumulative Causation (Myrdal, 1957) / Polarization (Hirschman, 1958) growth theory. Both Myrdal and Hirschman recognize the unbalanced growth among regions. Regions grow at different rates, such that richer regions grow at faster rates. This creates the gap that we see between richer and poorer regions. Myrdal named the economic relationships in between the richer and the poorer regions the "spread" and the "backwash" effects, while Hirschman called the relationships the "trickling-down" and the "polarization" effects.

In the spatial sense, economic growth does not appear everywhere at the same time. And once the magic of economic growth hits a place, the "friction of space" makes a spatial concentration of economic growth around that initial place. Therefore, in the process of economic development, regional economic centers are formed. These economic centers are the richer regions, while the periphery areas are usually the poorer regions (Hirschman, 1958). For Hirschman, the trickling down effect from economic centers to the periphery areas happens in two ways: first, the richer regions purchase goods from and invest in the poorer regions; second, the richer regions can absorb the surplus labor force from the poorer regions. The polarization effect also happens in two ways: one is the competition in capital investment and production; the other is the self-selected internal migration. Rather than absorb the unemployed labor force from the poorer regions, the richer regions are in fact gaining a more educated and more enterprising labor force from the poorer regions. Myral's concept is similar to Hirschman's. For the future of the poorer regions, Myrdal (1957) believed that the spread effect is weaker when compared to the backwash effect; therefore the inequalities between regions tend to accumulate. However, Hirschman believed that, in the end, the trickling-down effect would exceed the polarization effect if the richer regions have to rely on the products of the poorer regions. Myrdal's theory predicts divergence in between regions, whereas for Hirschman, the initial gap could still has a chance to be closed.

Williamson (1965) further extended Myrdal and Hirschman's theory to the economic development of regions within a nation. He argued that the evolution of regional inequality levels would follow an "inverted-U shaped" path. In the early stages of economic development, the more skillful and more educated portion of the labor force moved to the advanced regions to earn higher incomes. Capital also moved to the advanced regions in order to benefit from the effects of external and agglomeration economies. The policies of the central government also tend to be in favor of the more advanced regions in the interest of maximizing national development. In these cases, the inter-regional linkages are weaker during the early stages of development; therefore, the trickling-down from the advanced regions is limited. However, the gap between the per capita income levels of the two types of regions will not persist. According to Williamson, in the later stages of development, the labor migration is less selective; capital moves to the less developed regions to seek higher marginal returns, and the central government pays more attention to inter-regional transfers. Hence, Williamson suggested that the inequality level between regions tends to increase in the earlier stages of growth and decrease in the more mature stages of economic development.

Endogenous growth theory

After three decades of regional development practice following World War II, in the 1980s economists' research interests returned to Solow's model, and they tried to test whether Solow's prediction of income convergence was correct. The empirical results were mixed. The convergence results were mostly found within a set of richer countries. The gap between developed countries and developing countries was persistent. Thus, some researchers suggested an endogenous growth theory to challenge the validity of Solow's neo-classical growth model. According to the review paper by Martin and Sunley (1998), endogenous growth theory is a radical response to the shortcomings of the conventional neoclassical growth theory in that it introduces increasing returns into the production function.

The endogenous growth theory can be divided into three categories as they are focused on three aspects: increasing the range of capital (Romer, 1986), taking human capital into account (Lucas, 1988), and embodying technological change (Aghion & Howitt, 1990). Romer's key assumption is that knowledge spillovers can increase marginal productivity. Romer argues that current capital stock can motivate knowledge spillover and "learning by doing," and these externalities could accelerate technological progress and economic growth. Because of this new component of the production function, the marginal return to capital could be equivalent to, or bigger than, one. Thus, a region with a higher per capita income level may grow faster than a region with lower per capita income. However, federal government taxation and transfer payment could reduce the gaps in between regions.

Lucas introduced the component of human capital into the production function. In his view, technological progress comes from the accumulation of human capital through research and education. In this model, the sum of returns to human and traditional capital can be greater than one. Lucas' model predicts divergence. However, possible convergence can be achieved through public policy and human capital investment.

The last type of endogenous growth model is the Schumpeterian, or the innovation endogenous growth theory. Aghion and Howitt (1990) developed this model based on Schumpeter's theory of the process of creative destruction. In this model, the return to labor is equal to one. This model also predicts divergence. However, with technology diffusion, transfer payments, and imitation, less developed regions have the potential to catch-up.

The endogenous growth model raises two important questions for the convergence model. First, do regions actually converge toward each other, or do they diverge because of the possibility of a constant return or even an increasing return to scale? Secondly, how do technology diffusion and spillovers affect the regional growth pattern?

Business cycle and regional growth

Neo-classical theory implies convergence, while polarization and endogenous growth theories predict divergence. However, the forces of convergence and divergence always co-exist simultaneously. Decreasing marginal returns constantly push capital away from capital dense regions toward capital scarce regions. Further, the technology diffusion process also brings new technology to less developed regions. These are two examples of the forces of convergence. On the other hand, through technological innovation, the higher income regions can always find new growth engines, generating one of the forces of divergence.

This paper integrates the forces of convergence and divergence in a spatial-temporal framework. The key assumption is that innovation capacity varies by time and location. This research assumes that the higher income regions are more innovative than the lower income regions, and the rate of innovation is higher during a recession-recovery period than during a normal growth period.

From the spatial aspect, this assumption is consistent with Vernon's product cycle theory (Vernon, 1966). The product cycle theory states that new products are invented and made in more advanced regions in the beginning of their product cycles; the advanced regions retain the monopoly rents of the new products. When the new products become mature and standardized products, the less advanced regions will start to produce these products. Thus, the innovation occurs in advanced regions then spreads to less advanced regions over time. Also noted by Malecki (1997), innovation gap is a primary source of regional disparities. From the temporal scale, this assumption is consistent with Schumpeter's theory of business cycle and evolutionary economics (Schumpeter, 1939, 1947). According to Schumpeter's theory on evolutionary economics, the engine of capitalism is the process of creative destruction which is "incessantly destroying the old one, incessantly creating a new one." From an aggregated point of view, according to Schumpeter's theory of the business cycle, the recession in a business cycle is the time when many existing technologies and products have become obsolete, and the new technologies and products have not been invented. After a recession hits the economy, many firms and innovators try out new ways of doing things. Those who succeed will retain the monopoly rents and help lead the economy toward its normal growth trajectory.

Also from Schumpeter's point of view, there are different types of business cycles. Schumpeter suggested a model which has 4 types of business cycles according to the length of the cycle. The shortest business cycle is the 3-5 year Kitchin inventory cycle. The second is the 7-11 years Juglar fixed investment business cycle. The third is the 15-25 year Kuznets infrastructure investment cycle. The longest business cycle is the 45-60 year Kondratiev wave. These four types of cycles can be added together to form a composite waveform. Duijn (1977) provided evidence that a major recession or the Great Depression occurred when all four cycles coincide.

The focus of this research is the Juglar business cycle. However, it is important to understand both the short term business cycle and the long term business cycle. As shown in the later analysis, some patterns cannot be explained with the short term business cycle. In this situation, the long term business cycle provides another lens through which we can analyze the issue.

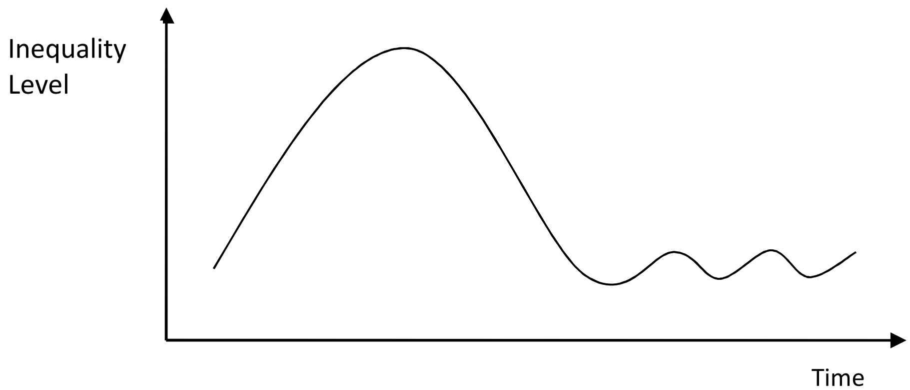
Research hypothesis and conceptual framework

Vernon's product cycle theory focuses on the spatial aspect of innovation, while Schumpeter's creative destruction theory focuses on the temporal aspect of innovation. Building on these two aspects, this study assumes that during a normal growth period, the primary reason that the higher income regions grow faster than the lower income regions is the monopoly rents from the new innovations that are created in the higher income regions. During a recession-recovery period, these monopoly rents no longer apply because the new products are now standard products. Therefore, the gap between the higher income regions and the lower income regions could increase during a normal growth period, because the forces of divergence could be stronger than the forces of convergence. For the recession-recovery period, the forces of divergence become weaker than they were in the normal growth period. The hypothesis of this research is that the regional convergence rates are lower in the normal growth periods and the regional convergence rates are higher in the recession-recovery periods. This hypothesis is tested by both the exploratory and the explanatory techniques.

The conceptual framework of this paper is an extension of the works by Williamson and Amos (Williamson, 1965; Amos, 1988). Williamson adapted Kuznets' hypothesis (Kuznets, 1955) about the inverted-U relationship of personal income to the regional level. He argues that, during the early stages of national development, regional income inequality increases. As the development progresses, the divergence force will decrease and the convergence force will increase. Hence, regional income inequality will decrease during the later stages of development.

Amos (1988) asked an important question that was brought up by Williamson's study: What would happen after the regional development process completes the inverted-U pattern? Would the regional income inequality stabilize? Or would the regional income inequality begin to increase? His research presents support for the case that the regional income inequality increases in the latter stages of development.

However, the study presented here argues that, when the economy is in an advanced stage, having moved from significant disparities to greater equality, the regional inequality level will not always stabilize – it can continue to increase and decrease. I assume that both of these two circumstances could occur and as indicated in Figure 2.1, the period of increasing and the period of decreasing can occur one after the other and continue to do so into the future. This figure resembles a big inverted-U shape followed by many smaller inverted-U shapes. According to the research hypothesis stated above: the increasing and decreasing of regional inequality level is associated with the business cycles.



Conceptual Model - Inequality Level Changes Over Time

Therefore, by using the standard convergence regression equation, I would expect to capture different convergence rates for different periods in the business cycle: a higher convergence rate during a recession-recovery period and a lower convergence rate during a normal growth period. This is the empirical objective of this study.

This study does not attempt to construct a new theory to describe the regional economic development pattern. Instead, it uses the existing theories and existing empirical techniques to understand the regional growth patterns in the context of short-run business dynamics. The empirical tests used in this paper confirm the hypothesis that the gap between the richer regions and the poorer regions increases during the normal growth periods. By understanding the growth pattern under different economic environments, this study argues that the federal government should pay more attention to poorer regions when the overall national economy is booming.

3. Determine the spatial and temporal scales of analysis and exploratory analysis

In this section, I first define the spatial and temporal scale of analysis. Then I apply spatial exploratory data analysis techniques to analyze the changes in regional income in the United States. The purpose of the exploratory analysis is to provide an overall understanding of the regional economic growth patterns and to set the base for the econometric analysis in sections 4 and 5.

Define the spatial scale of analysis

The population and personal income data used in this paper are derived from the Regional Economic Information System (REIS) which is a regional economic database provided by the U.S. Bureau of Economic Analysis. The REIS provides state level data starting from the year 1929 and county level data starting from the year 1969. The first issue to address is to decide which spatial unit to use for the analysis. Most convergence studies have focused on the state level. However, the state level is still too large a unit to reflect the local labor market dynamics. For example, Upstate New York has a totally different demographic and economic structures when compared to the New York Metropolitan area. The same situation happens in the State of Illinois: the Chicago Metropolitan area is completely different from Downstate Illinois. The other commonly used spatial unit is the county level. However, the county level analysis may raise problems, because the county boundary is merely an arbitrary political boundary. It does not reflect the economic structure of a region. A county may be only a part of an economic or labor market area. For example DuPage County, Illinois, is only a part of the Chicago Metropolitan area.

Therefore, instead of using the county level data directly, this research aggregates the county level data to the commuting zone level. Commuting zones are integrated economic areas. This spatial unit was developed by the U.S. Department of Agriculture (USDA) in order to better understand the economic and social diversity of the metropolitan and the non-metropolitan

American. The USDA identified 741 commuting zones[1] based on the 1990 census journey-to-work data. Compared with the relatively arbitrary county boundaries, commuting zones are much more useful for analysis because they represent the supply and the demand of labor in the local labor market. This study focuses on the continental part of the U.S., which includes 719 commuting zones. Figure 3.1 shows the commuting zones in the continental U.S.

Define the temporal scale of analysis

Earlier, it was noted that the regional growth patterns are different under two types of economic conditions: the recession-recovery period and the normal growth period. The definitions of these two periods in this study are not exactly the same as the business cycle definition used by the U.S. National Bureau of Economic Research (NBER). The economists in the NBER identify the peaks and troughs of the economy. The period in between a peak and the following trough is called a recession period, and the subsequent period from a trough to a peak is called an expansion period. By the NBER's identification, the years from 1969 to 2007 were broken into 6 recession periods and 6 expansion periods. Some periods lasted less than 12 months. For our purpose, it is not meaningful to measure the regional growth trends under such short periods. Therefore, based on the NBER's definition, this research defines its own recession-recovery period and normal growth period.

Different from the NBER's definition, the definitions used in this paper are based on the nonfarm employment level. This job based measurement has a major advantage over the productivity based measurement used by the NBER, because increasing productivity does not always equate with a return to a growth trajectory. For example, the NBER declared that the recession associated with the housing and financial market meltdown lasted from December 2007 to June 2009. This means that after June 2009, the U.S. economy was starting to expand again. However, most U.S. consumers do not agree with the statement that the economy is getting better. According to the Survey of Consumers Report by Thomson Reuters/ University of Michigan, the confidence of consumers in September, 2011 is at a very low level, similar to what it was in 2008 and 2009. Moreover, consumers are expecting the economy to continue to

[1] For more information about commuting zones, please refer to USDA website at http://www.ers.usda.gov/briefing/rurality/lmacz/

stagnate at its current depressed level. Therefore, productivity recovery without job recovery may not be regarded as a "real" recovery. Thus, in this study, I define the recession-recovery periods and the normal growth periods based on changes of jobs that are reported by the U.S. Bureau of Labor Statistics.

The concepts of normal growth period and recession-recovery period are similar to the four stages for the Juglar cycle. According to Schumpeter (Schumpeter, 1994), a 7 to11 year Juglar fixed investment cycle has four stages: expansion, crisis, recession, and recovery. The normal growth period in this paper is similar to the expansion stage. And the recession-recovery period is similar to the recession and recovery stages in the Juglar cycle. The crisis stage is a short time period in between a normal growth period and a recession-recovery period.

The recession-recovery period includes the recession period and the recovery period. I define a recession period as the period when the number of nonfarm laborers is between the peak of the economy and the trough. I define a recovery period as the period when the number of nonfarm laborers rises from the trough up to about 4-7 percent[2] more than to the previous peak[3]. Thus, a recession-recovery period lasts from one peak to the next trough and from that trough to a point in time when the nonfarm employment is 4-7 percent more than the previous peak. Finally, a normal growth period lasts from the end of a recession-recovery period to the next peak. The advantage of using this definition of the recession-recovery period is that by imposing a 4-7 percent recovery from the previous peak, it indicates that the economy is back to its normal growth track and the economy has found its new growth engine.

Using these definitions, this research identifies six time periods. The first is the energy crisis period, ranging from 1973 to 1980. Between the years 1973 and 1980, there was a recession-recovery period and a normal growth period. However, there was a common driving force during this time period: the rising energy price. The rising energy price had a significant impact on the regional growth pattern. Thus, I group 1973 to 1980 together to study the effect of the energy crisis on regional economic growth pattern. Then, from 1980 to 1984 is a recession-recovery period. Next, 1984 to 1990 was a normal growth period of six years. The key force

[2] The benchmark employment level is January 1969. The employment level in January 1969 is set as 100 percent.

[3]The employment data is monthly data, while the income data is annual data. Thus, in this paper a value range of employment level is used to identify the cutoff time. In this case 4-7 percent range is chosen because it represents a significant growth after the recession.

behind this growth period was President Reagan's policy to encourage entrepreneurship by cutting taxes. From 1990 to 1994 is another recession-recovery period. This was followed by a normal growth period of seven years, from 1994 to 2001, which was mainly driven by the growth in the information and communication technology sector. From 2001 to 2007 was a recession-recovery period that went along with the nation-wide decline in the manufacturing and information sectors. The 2001-2007 recession-recovery period differs from those of 1980-1984 and 1990-1994 because the year 2007 is still not the end of this recession-recovery period. In fact, according to our definition, the national economy has still not recovered even in the year 2011. Thus we will refer to the period 2001-2007 as the recession-recovering period. Figure 3.2 shows the nonfarm employment growth in U.S. and the classification of the six periods.

Exploring the overall growth pattern

In 1929, 4 regions (Mideast, Far West, New England, and Great Lake) had initial incomes that were above the U.S. average, and 4 regions (Southeast, Southwest, Plains, and Rocky Mountain) had initial incomes that were below the U.S. average (table 3.1). The gap between the wealthiest region (Mideast) and the poorest region (Southeast) was 87% of the U.S. average income in 1929. In 1969, the pattern was similar, but the gap between the wealthiest and the poorest regions declined to only 35% of the U.S. average income. In 2007, all the regions have above 90% of the U.S. average income. However, the Great Lake region's per capita income level dropped to be less than the national average. This first glance of per capita income data shows that the regional income levels were converging in the last century.

One of the most powerful and straightforward approaches to examining the regional growth pattern is to plot the kernel density function for the per capita income distributions (Quah, 1996). According to Quah (1996), in the process of regional income convergence, the income distribution could change from a one-peak to a two-peak mode. These two peaks represent two convergence clubs: the rich club and the poor club. However, figure 3.3 shows a different pattern compared with the pattern Quah (1996) discussed in his paper: over time, the distributions are changing from two-peak to one-peak. For the year 1973, the income distribution clearly shows two peaks. Over time, the kernel density functions become more and more concentrated in the middle and the two peaks converge into one peak. For the year 2001, the concentration achieves the highest level. From 2001 to 2007, the level of concentration decreases and the distribution again has two peaks. Therefore, the U.S. commuting zone level data shows a converging and then diverging pattern.

Exploring the spatial growth pattern

The Moran's *I* is used here to examine the overall spatial autocorrelation of per capita income levels. The Moran's *I* can be seen as an analogue to the measurement of correlation in time series:

$$Moran's\ I = \frac{N}{\sum_i \sum_j w_{i,j}} \frac{\sum_i \sum_j w_{i,j}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i \sum_j (x_i - \bar{x})(x_j - \bar{x})} \quad (1)$$

In this equation, *N* is the number of total spatial units, and they are indicated by *i*, and *j*. $w_{i,j}$ is the spatial weight matrix, x_i is the value of the interested variable for the spatial units *i* and $\bar{x}$ is the mean of this variable. The Moran's *I* for the county level per capita income and the commuting zone level per capita income are shown in figure 3.4. At the county level, the Moran's *I* is between 0.068 and 0.182, while at the commuting zone level, the Moran's *I* is in the range of 0.331 to 0.653. This means that the commuting zones are more spatially dependent on each other. The spatial relationships between counties are not as large. This difference is as expected. Commuting zones are more internally homogenous within the area, but heterogeneous with respect to their neighbors, generating a higher measurement of spatial autocorrelation than was the case for individual counties. On the other hand, counties are defined by arbitrary political boundaries, and they are more homogenous with their neighbors. This leads to a low measurement of spatial autocorrelation.

At the commuting zone level, the overall trend for spatial autocorrelation is decreasing over time. A decreasing value of Moran's *I* means that, over time, the income level of one commuting zone depends less on the income level of its neighboring commuting zones. A small (but still positive) value of Moran's *I* means that being close to a rich region does not guarantee that your region will also be rich. So the spatial pattern of personal income level is moving from more spatially correlated to more spatially scattered.

Moran's *I* is a global measure of spatial association. It does not provide information with respect to each individual's spatial autocorrelation level. The more localized measure is the "local indicator of spatial association" (LISA) (Anselin, 1995). It is used here to explore the spatial patterns of regional growth. The figures in the appendix show LISA maps for per capita income level in seven time points (1973, 1980, 1984,1990,1994, 2001, and 2007), and the per capita income growth in these six sub-periods (1973-1980, 1980-1984, 1984-1990, 1990-1994, 1994-2001, 2001-2007) and the entire period (1973-2007).

The figures (figures A1a to A1g) on the left hand side are seven LISA maps for per capita income level, and the figures (figures A2a to A2g) on the right hand side are seven LISA maps for per capita income growth. In the LISA maps, the dark red areas and the dark blue areas indicate the high value and the low value clusters, respectively. In the LISA maps for per capita income level (figures A1a to A1g), a dark red area means that the area has a high income level and its neighbors also have high income levels as well. On the other hand, a dark blue area shows that the area has a low income level and its neighbors have low income levels, too. The interpretations for per capita income growth LISA maps (figures A2a to A2g) are different. In this case, a dark red area means that the area has a high income growth rate and its neighbors also have high income growth rates. The dark blue area can be explained as an area with a low income growth rate and surrounded by low income growth neighbors.

Two points are clear from the income level maps: first, the low income clusters are declining in the South East and secondly, three high income level clusters are consistent - they are the Boston-New York-DC area, southern Florida, and the California coast area.

The income growth LISA maps (figures A2a to A2g) reveal more dynamic stories. An energy crisis and an agriculture crisis occurred in between 1973 and 1980. Figure A2a clearly shows these two trends. On one hand, there are three red color high growth clusters; these are the energy producing regions. On the other hand, there is a huge slow growth cluster, and it is mostly in the agriculture-related Plains region. In 1980-1984, a recession-recovery period, part of the Plains region, which previously had slow growth, now shows a high growth rate, while most areas in the Rocky Mountains and Far West show slow growth. In 1984-1990, a normal growth period, the South East and Boston-New York-DC show high growth rates. The recession in the early 1990s was also energy related, thus the fast growth clusters show up in the energy producing regions in the South as expected. The period from 1994-2001 has a few high growth clusters. And during the last period, 2001-2007, the Great Lakes and part of the South is declining. Figure A2g shows the overall growth clusters from 1973 to 2007, and the clearest pattern is that south grew faster over the entire period.

In this section, I explored six periods in the U.S. regional income changes. Through the exploratory analysis, it becomes clear that there are some differences in income growth patterns between a recession-recovery period and a normal growth period. In recession-recovery periods, the variation among regional income decreases and the regional spatial autocorrelation decreases, but *vice versa* for normal growth periods. An absolute convergence model and two spatial convergence models are presented in the next section. These models will be used in section 5 to test whether the recession-recovery periods have higher convergence rates than the normal growth periods.

4. The β-convergence model with spatial effect

Both exploratory analysis and explanatory analysis are used in this research. The exploratory analysis part in section 3 suggested the appropriate spatial scale and time periods of our analysis. This section is focused on the β-convergence model that will be used for the explanatory analysis in section 5.

Recall that the goal of the paper is to capture the temporal variation in convergence rate under different economic conditions. There are two widely used convergence measures: σ-convergence and β-convergence. σ-convergence stands for the decline in inequality among regional personal income levels. We use the coefficient of variation to indicate σ-convergence. Meanwhile, β-convergence implies that the growth rates for poorer regions are faster than those for wealthier regions.

There are two sets of concepts here: equality/inequality and convergence/divergence. σ-convergence is related to the equality/inequality argument, while β-convergence is related to the convergence/divergence argument. According to Furceri (2005), many empirical researchers found that a necessary condition for the existence of σ-convergence is the existence of β-convergence in the data. Furceri also mathematically proved that decreasing inequality certainly implies convergence. However, convergence implies decreasing inequality only under certain conditions. Thus σ-convergence is a stronger condition than β-convergence. The explanatory analysis in this paper is focused on testing the convergence argument by using the β-convergence model.

The β-convergence model in this paper follows Barro and Sala-i-Martin's specification (Barro & Sala-i-Martin, 1992).

$$\ln\left(\frac{y_{i,t}}{y_{i,0}}\right) = a - (1 - e^{-\beta T})\ln(y_{i,0}) + \varepsilon_{i,t} \qquad (2)$$

In this equation: $y_{i,t}$ is the per capita income for region i at year t; $y_{i,0}$ is the per capita income for region i at year 0; α is the constant term; β is the convergence rate; $\varepsilon_{i,t}$ is the error term. In this paper, I did not use any other control variables because all the study areas are within the same country. So the absolute β-convergence model is tested in this research. When β is significant and greater than zero, there will be β-convergence. When β is significant and less than zero, there will be β-divergence.

Baumol (1986) was among the first to test the convergence model. He tested the unconditional convergence hypothesis by using the per capita income data from the sixteen richest countries from 1870 to 1979. He found that countries with lower level per capital income do tend to grow faster. This is strong evidence to support the unconditional convergence hypothesis. However, the data for Baumol's research has a "selection bias" problem. All the countries in his sample have high per capita incomes. When adding more countries to this sample (De Long, 1988), the negative relationship between initial per capita income and the growth rate become insignificant. Empirical tests based on a larger set of countries in a shorter time period such as those using the Summers-Heston data set do not find evidence to support the unconditional convergence hypothesis either (Ray, 1998, p. 81).

The empirical tests based on regions within a country and the European Union provide strong support for the unconditional convergence hypothesis. The most influential study is by Barro and Sala-i-martin (1992). They studied the convergence across US states and found significant evidence to support convergence. In a more comprehensive study by Sala-i-Martin (1996), regional convergence for US, Japan, and five European regions was explored. He found that the income levels of these regions converge at about two percent per year.

Neoclassical growth theory implies that capital deepening is the source of convergence. While endogenous and polarization growth theories point out that there are other sources of convergence, such as technological diffusion and factor mobility. Both technological diffusion and factor mobility are related to the spatial location of the region. However, most early studies treated regions as isolated islands that had no influence on each other. This type of conventional convergence modeling ignored the spatial effect on regional growth and could produce a biased result.

The spatial lag and spatial error models are two ways of modeling the spatial interaction effect (Anselin, 1988). In the regional growth context, the spatial lag model will detect whether the growth rate of one region is related to the growth rates of its neighboring regions. The spatial lag β-convergence model is as follows:

$$\ln\left(\frac{y_{i,t}}{y_{i,0}}\right) = a - (1 - e^{-\beta T})\ln(y_{i,0}) + \rho W \ln\left(\frac{y_{i,t}}{y_{i,0}}\right) + \varepsilon_{i,t} \qquad (3a)$$

$$\ln\left(\frac{y_{i,t}}{y_{i,0}}\right) = (1 - \rho W)^{-1}[a - (1 - e^{-\beta T})\ln(y_{i,0}) + \varepsilon_{i,t}] \qquad (3b)$$

In equation 3*a*, $W\ln\left(\frac{y_{i,t}}{y_{i,0}}\right)$ is the spatial lag of growth rate; the *W* is the spatial weight matrix, and ρ is the coefficient of spatial correlation. In addition to the conventional β-convergence model, the spatial model added the term $\rho W\ln\left(\frac{y_{i,t}}{y_{i,0}}\right)$ as an independent variable. This term shows that the growth rates from the neighboring regions could affect the growth rate of the studied region. However, we cannot estimate equation 3*a* directly, because the natural log of the growth rate appears in both sides of the equation. Therefore, we move $\rho W\ln\left(\frac{y_{i,t}}{y_{i,0}}\right)$ to the left hand side, multiply the system by $(1-\rho W)^{-1}$, and we get equation 3*b*. This equation can be estimated using the maximum likelihood estimation method. The important message coming from this model is with regard to ρ. If ρ is positive and significant, it means that the growth rate for the neighboring region has a positive effect on the studied region. Therefore, a high growth rate in one region will have a positive effect on the neighboring regions' growth rates.

The other spatial model proposed by Anselin is the spatial error model. In contrast with the spatial lag model, the spatial error model will detect whether the above or below average growth rates of neighboring regions will have an impact on our study region's growth rate. The spatial error β-convergence model can be written as:

$$\varepsilon_{i,t} = \lambda W \varepsilon_{i,t} + \mu_{i,t} \qquad (4a)$$

$$\varepsilon_{i,t} = (1 - \lambda W)^{-1}\mu_{i,t} \qquad (4b)$$

$$\ln\left(\frac{y_{i,t}}{y_{i,0}}\right) = a - (1 - e^{-\beta T})\ln(y_{i,0}) + (1 - \lambda W)^{-1}\mu_{i,t} \qquad (4c)$$

Here equation 4*a* demonstrates that the original error term from the conventional β-convergence model could be correlated with the error terms from the neighboring regions. We rewrite equation 4*a* to 4*b*. In equation 4*b*, the error term $\mu_{i,t}$ satisfy the i.i.d. assumption. Therefore, equation 4*c* will yield an unbiased estimator for β. If the parameter λ from the spatial error model is significant, it will tell us that a shock occurring in one region would affect the growth rate in the neighboring regions.

It is important to distinguish these two types of spatial models because they imply different types of economic policies to promote growth. According to Bernat (1996), the spatial error model implies that a region's growth is affected by neighboring regions only if the neighboring regions have above or below normal growth rate; on the other hand, for the spatial lag models, one region's growth is directly affected by a neighboring region's growth.

These two types of spatial models also provide different insights into the geographic aspect of the growth model. From the aspect of the spatial lag model: when growth occurs in one place, it will affect the growth rate of its neighboring regions. When the neighboring regions start to grow, they will affect their neighbors. Therefore, growth is a sprawl process. On the other hand, the spatial error model focuses more on random shocks. The "magic" of economic growth will hit a region, and this growth effect will spread to its neighboring regions. Further, the random shocks could happen in different places and at different times. Therefore, the similarity between the spatial lag and spatial error models is that they both demonstrate that economic growth will spread to neighboring regions. The difference between these two models is that the spatial error model demonstrates that economic growth is a random shock and it could happen anywhere, anytime.

Rey and Montouri (1999) were among the first to include the spatial effect in the neoclassical convergence model. They tested the spatial autocorrelation of per capital income among U.S. states, and concluded that the income for one state is influenced by its neighboring states. Then they proposed a spatial version of the absolute β-convergence model and tested the spatial lag and spatial error models. According to their estimations, the spatial error model shows a better performance when compared to the spatial lag model.

As Fingleton and Lopez-Bazo (2006) pointed out, Rey and Montouri and many other researchers who used the spatial econometrics in their growth models did so in a rather *ad hoc* manner. They lack the theoretical background and fail to address the key problem: why the empirical spatial model is favored over the spatial error model. Lopez-Bazo, *et al*. (2004) showed that if we assume that the technological level in one region impacts its neighboring regions, then the technology spillover will not affect the convergence rate β. They also showed that, according to their model, the spatial error model is the preferred model specification.

There are two reasons to introduce the spatial econometric models into this research. First, they can help us to correct the biased estimation problem raised from spatially correlated observations. Secondly, by identifying which spatial econometric model is the preferred specification, it will help us to understand what kind of policy we need to use to promote regional development.

5. Estimation results

The goal of this paper is to test the hypothesis that regional convergence rates are higher in recession-recovery periods than in normal growth periods. The absolute β-convergence model, as described in section 4, is used to test this hypothesis. In this section, three econometric methods are applied to the absolute β-convergence model to investigate the convergence or divergence debate for the six sub periods I identified in section 3. The Ordinary Least Square (OLS) regression method is the basic way to test the relationship in between regions' growth rates and their initial income levels. However, the OLS regression could be biased when dealing with spatial data. Therefore, the spatial econometric models are used to correct this bias. And finally, quantile regression is used here to provide a more detailed picture of the various convergence or divergence behaviors for regions based on different growth quantiles.

OLS regression

The OLS estimation results for the absolute β-convergence model (specified in equation 2) of 719 continental commuting zones are shown in table 5.1. In the energy crisis and the two recession-recovery periods, the overall goodness of fit of this single variable regression is fairly high; the adjusted R^2 are 29.31%, 20.05%, and 17.74%, respectively. The other three periods, 1984-1990, 1994-2001, and 2001-2007, the overall goodness of fit of the regression is quit poor, with the adjusted R^2 1.29%, 0.31%, and -0.12%, respectively. This implies that the absolute β-convergence model may not be appropriate for these three periods.

For the variable in interest, the first four periods yield statistically significant β-convergence rates. The results for the last two time periods are not statistically significant at the 5% level. For the first four periods, 1973 to 1994, the regressions demonstrate strong evidence for convergence, and the convergence rates are 8.87%, 6.78%, 0.81%, and 3.34%, respectively. However, for the period 1994 to 2001, the convergence rate is negative and the p-value is 0.072. This result suggests that regional income divergence is indicated in this period. The absolute convergence model for the period 2001-2007 shows no statistically significant relationship between initial income levels and growth rates. In order to compare, I also estimate the β-convergence model for the entire time period of 1973-2007. The adjusted R^2 is the highest among all models, and the convergence rate is 1.80%.

The regression results are as expected. From 1973 to 1980 is the period when the United States was suffering from the first energy crisis. High energy prices had a varied effect on different regions. On the one hand, high energy prices drove up the cost of living and the cost of production. On the other hand, for the energy production regions (like the South, Appalachian, and mountain regions, where they have coal or oil resources), the high energy prices yielded more of an advantage in economic growth during this period. Hence, the convergence rate in this period is the highest at 8.87% a year. The other 2 periods with strong convergence tendency are two recession-recovery periods 1980-1984 and 1990-1994. They have very high convergence rates at 6.78% and 3.34%, respectively.

The first normal growth period, 1984-1990, has a very small but statistically significant convergence rate at 0.81% a year, while the second normal growth period, 1994-2001, has a -0.33% divergence rate. This pattern gives support to our hypothesis that the recession-recovery periods have higher convergence rates than normal growth periods. The normal growth period may even have regional income divergence.

For the recession-*recovering* period, 2001-2007, the coefficient is not statistically significant. It is not clear why the recession-*recovering* period of 2001-2007 does not show any sign of convergence or divergence. According to our hypothesis, it should have a relatively high convergence rate. One possible way to look at this issue is by using the theory of the long term, Kondratiev business cycle. The U.S. economy has been going through a fundamental change since 2000. This period could be a Kondratiev recession or depression period. It is out of the scope of this paper to identify the effects of the long term business cycle on convergence testing. The second possible explanation could be that this recession-*recovering* period is fundamentally different from the other two recession-recovery periods. In 2001-2007, the employment level never recovered according to the recovery definition used in this paper.

Spatial econometric models

As indicated before, only using the OLS procedure without considering the spatial interdependence of the study areas will lead to biased results. Table 5.2 shows the spatial autocorrelation test for the pervious OLS regression model. The spatial weight matrix used here is a row standardized first order queen contiguity matrix. Moran's *I* test (column 4 in table 5.2) for the residual spatial autocorrelation shows that for all the time periods, there is strong evidence for the presence of spatial autocorrelation. However Moran's *I* test does not distinguish between the two forms of spatial misspecifications described in section 4. Robust tests against spatial error autocorrelation and spatial lag autocorrelation are also reported here. According to Anselin *et al*. (1996) these two robust tests demonstrate high power against alternative specifications.

The robust test results for all six periods are as expected (column 2 and 3 in table 5.2). They clearly point to spatial error models as preferred specification. The robust test *p*-value for spatial error models are 5% significant for five out of six periods except 1984-1990, while only 3 periods are significant under the spatial lag specification. The period 1984-1990 does not show significant test results using either the spatial error or spatial lag models, while the whole time period 1973-2007 suggest the use of the spatial lag model rather than the spatial error model.

The importance of distinguishing the spatial error model from the spatial lag model is that they imply different ways to influence neighboring regions' growth rates. The spatial lag model means that a region's growth is directly affected by its neighbors' growth. It is more of a spatial spillover effect. However, for the spatial error model, the spatial effect is more of a random shock effect. This means that the abnormal growth rate in one region will have a spatial effect on the neighboring region. Therefore, it is understandable that in the long run (1973-2007), the robust test points us to the spatial lag model; while for the short run, the robust test points us to the spatial error model in four out of six cases.

Table 5.3 reports the estimation results from two spatial econometrics models. In order to better compare with the OLS estimation, I put the results from table 5.1 in this table as well. Based on the Akaike information criterion (AIC), all the spatial models have smaller AIC values than for the OLS estimation; this means that spatial regression achieved a better fit than the OLS regression.

Based on the theoretical model by Lopes-Bazo *et al*. (2004), the spatial error model should be a better specification for convergence model. Empirical results also support this argument (Fingleton & López-Bazo, 2006; Rey & Montouri, 1999). In this research, the diagnostic test shows in favor of the spatial error test, the AIC supports the same conclusion that four out of six periods are in favor of the spatial error model.

Figure 5.1 plots the β-convergence rates for above three estimations. Compared with the normal growth periods (1984-1990, and 1994-2001), the recession-recovery periods (1980-1984, and 1990-1994) have much higher convergence rates in all three estimations. The estimations from the spatial error and spatial lag models are lower than the estimation results from OLS. In the periods 1973-1980, 1980-1984, and 1990-1994, when the robust error test and robust lag test are highly significant, the difference in between spatial models results and the OLS estimation results are quite large.

After estimating the spatial lag and spatial error β-convergence models, I chose the convergence rate for each period using the minimum AIC standard: 1973-1980 is 6.20% (spatial error), 1980-1984 is 5.65% (spatial error), 1984-1990 is 0.47% (spatial lag), 1990-1994 is 2.11% (spatial lag), 1994-2001 is -0.59% (spatial error), 2001-2007 is -0.30% (spatial error), and for the entire period 1973-2007 is 0.76% (spatial lag). Estimating the spatial error and spatial lag models does not change the conclusion from the OLS estimation. However, the spatial error and spatial lag models provide more precise estimation results.

Quantile regression

Quantile regression can provide a more complete picture of the effect of the initial income on the region's income growth rate. While the Ordinary Least Squares is measured against the conditional mean of the dependent variable to the given independent variables, the quantile regression can estimate against median or any other quantiles of the dependent variable (Koenker & Hallock, 2001). As suggested by Mello and Perrelli (2003), using quantile regression to estimate the β-convergence model has two advantages: first, compared with OLS regression, quantile regression can provide more robust estimation results when the outlying observations are present in the data; second, quantile regression can capture parameter heterogeneity. This second advantage is especially useful for the conditional β-convergence model because quantile regression can identify the heterogeneous effects of the policy variables.

In the absolute β-convergence model, quantile regression can tell us: given study area income levels, how the growth performances vary across different quantiles of income growth rates. Figure 5.2*a* compares the results from quantile regressions with the OLS estimation for the β-convergence model. The red horizontal line is the OLS result, while the red dashed lines are the 95% confidence interval for the OLS estimation. The black dashed line indicates estimation results for different quantiles, while the gray area around the black dashed line is the 95% confidence interval for the quantile regression; care should be taken in the interpretation of the results. They are not β values, instead they are the values of $-(1-exp(-\beta T))$. Therefore, low value of $-(1-exp(-\beta T))$ means high value of β. Figure 5.2*b* translates the coefficients into β-convergence rates.

As show in figure 5.2, four periods (1984-1990, 1990-1994, 1994-2001, 2001-2007) have similar estimation results when the quantile regression is compared with the OLS estimation. For these four periods, the 95% confidence intervals for quantile estimation and OLS estimation overlap. However, for periods 1973-1980, 1980-1984, and the full period 1973-2007, the quantile regression and the OLS estimation give significantly different results.

For the entire period 1973-2007, the OLS underestimates β-convergence rate for lower quantiles (less than 50%). On the other end, the OLS significantly overestimates the β-convergence rate for the highest quantile (90%). Given that the β-convergence rate for the entire period 1973-2007 is 1.80% according to spatial lag, the convergence rate for regions with slower growth regions should be higher than 1.80%, while the convergence rates for regions with the highest growth rates should have lower convergence rate than 1.80%.

Two other cases are also very interesting: one is the 10% quantile in the period 1973-1980, and the other is the 90% quantile in the period 1980-1984. They both have very high β values, but for different reasons. In figure 5.3, I plot the log of starting year income to the income growth rate for these three cases. The red line is the OLS regression line. The black lines are regression lines for different quantiles, while the blue line is the regression line for median quantile. In period 1980-1984, the 90% quantile's high convergence rate was mostly driven by high growth rate in the lower income group. While in year 1973-1980, the high convergence rates in the lower quantiles were mostly driven by low growth rates in the high income areas.

Similar to using the spatial models, the quantile regression also supports the patterns that are found in the OLS regression. However, the quantile regression gives a clearer picture with respect to which group of regions were major driven force for different convergence behavior. For example, for 1973-1980, the driven force is that some high income regions were growing very slow. But for 1980-1984, the major driven force for high convergence rate was because some low income regions were growing very fast.

Quantile regression can be used as a new way to identify convergence clubs, and quantile regression can also contribute to the distributional dynamic approach developed by Quah (1996). As discussed in Mello and Perrelli (2003), the concavity pattern of their quantile regression results indicate the existence of convergence clubs among countries. In my quantile regression analysis, 1973-1980 and 1980-1984 also show concave patterns (see figure 5.2*a*). In the case of 1973-1980, some former high income areas had negative growth rates and joined the “low income club” (figure 5.3, 1973-1980). In the case of 1980-1984, some former low income areas had high growth rates and joined the “high income club” (figure 5.3, 1980-1984).

However, the long trend (1973-2007) quantile regression result shows a convex pattern (figure 5.2*a*, P1973_2007). This could be an indicator of disappearing convergence clubs. Recall the discussion in section 3 about kernel density functions: the per capita income distributions change from a two-peak to a one-peak mode. In figure 5.3_1973-2007, the income growth rates for formerly low income regions are relatively concentrated, while the income growth rates for the formerly high income regions are more dispersed. In the long run (1973-2007), the formerly poorer regions have higher growth rates compared with some of the formerly richer regions. However, some of the formerly richer regions still keep relatively high growth rates. This can be an indicator of the formation of a new rich club (see figure 3.3, year 2007).

6. Conclusion and policy implications

The exploratory and the explanatory analysis of growth patterns for different time periods clearly show that business/innovation cycle matters for the convergence test. Two recession-recovery periods in 1980-1984 and 1990-1994 show relatively high convergence rates. While two normal growth periods in 1984-1990 and 1994-2001 show a close-to-zero convergence rate and a negative convergence rate (divergence), respectively. The energy crisis period 1973-1980 shows a high convergence rate, and it is driven by the low growth rate of high-income regions. The recession-*recovering* period 2001-2007 does not show neither convergence nor divergence pattern.

The goal of this research is to understand the short term growth dynamics. This paper shows that there are dramatic differences in convergence rates under different economic situations. This paper also shows that quantile regression is a very useful tool to understand growth dynamics. It can help us to identify which group is the major contributor of the convergence/divergence.

This study shows evidence that the gap in between more developed regions and less developed regions was increasing during normal growth periods. This means that less developed regions do not grow as fast as more developed regions do when the economy was booming. This finding challenges the validity of the trickling down hypothesis in the later stages of economic development. The trickling down does not happen automatically. Therefore, at the latter stages of economic development, the federal government should still pay attention to the regional inequality issues.

This study only examines the relationship in between convergence pattern and economic cycles for the United States. Future research can test whether this relationship exists in other regions, for example, the European Union or the Japanese regions. Cross country/region comparison will enrich our understanding for the spatial and temporal variations for economic growth patterns.

Tables and figures

Figure 3.1. U.S. Commuting Zones
Source: USDA, http://www.ers.usda.gov/briefing/rurality/lmacz/

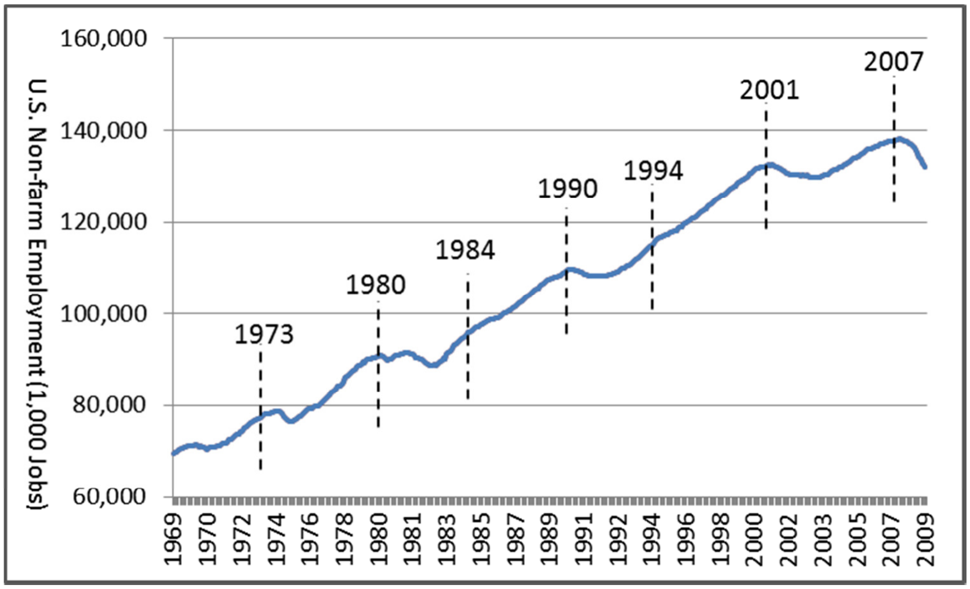


Figure 3.2. U.S. Employment Growth and Define the Periods

Source: U.S. Bureau of Labor Statistics, Current Employment Statistics, http://www.bls.gov/data/

Note: Name for each period

1973-1980	the energy crisis period
1980-1984	recession-recovery
1984-1990	normal growth
1990-1994	recession-recovery
1994-2001	normal growth
2001-2007	recession-recovering, the employment level is not recovered at 2007

	1929		1969		2007	
	Income	% of U.S.	Income	% of U.S.	Income	% of U.S.
United States	698		3,836		38,615	
New England	872	125%	4,185	109%	47,221	122%
Mideast	967	139%	4,318	113%	45,058	117%
Great Lakes	795	114%	4,040	105%	36,318	94%
Plains	566	81%	3,585	93%	36,661	95%
Southeast	364	52%	3,071	80%	34,859	90%
Southwest	472	68%	3,320	87%	35,768	93%
Rocky Mountain	589	84%	3,428	89%	36,527	95%
Far West	905	130%	4,409	115%	41,056	106%

Table 3.1. Per Capita Income ($ in real term)
Source: Bureau of economic analysis, Regional Economic Information System, http://bea.gov/regional/reis/

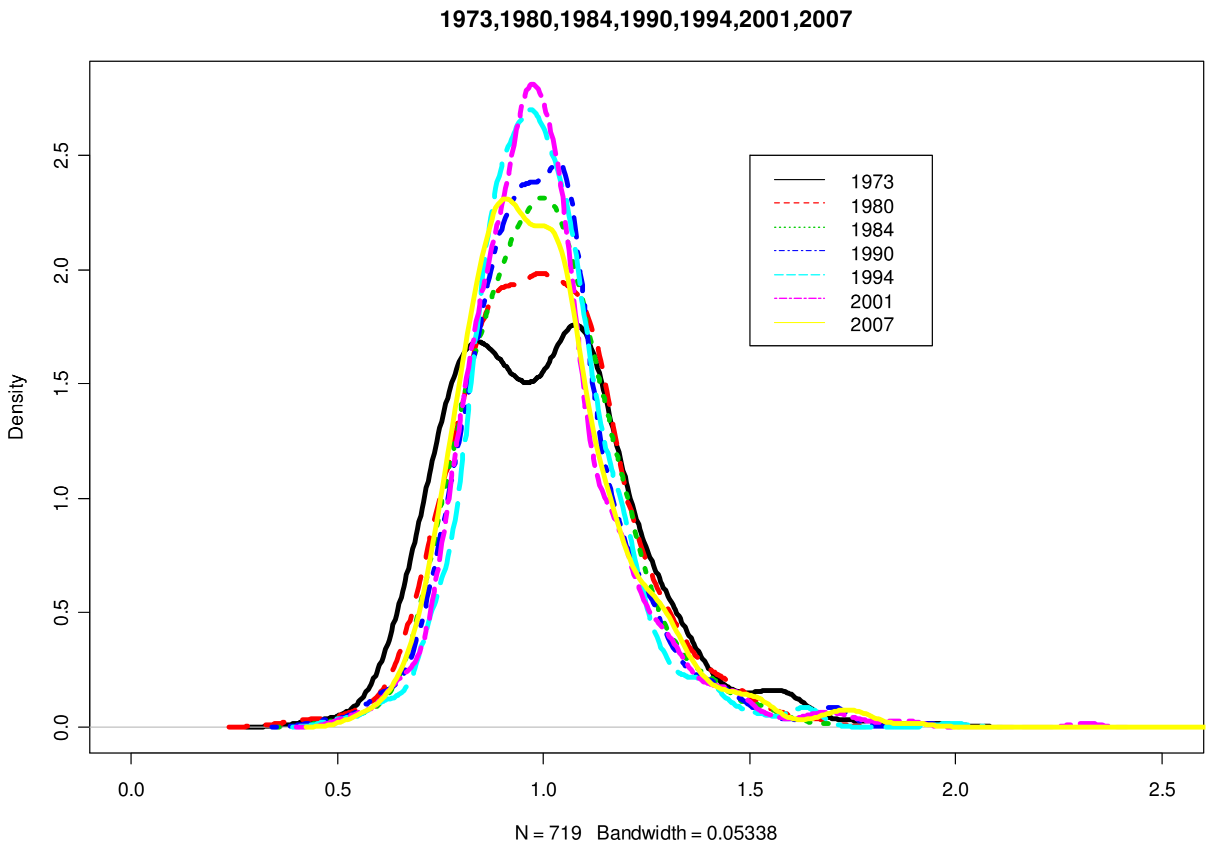


Figure 3.3. Commuting Zone Level Per Capita Income Distribution Dynamics

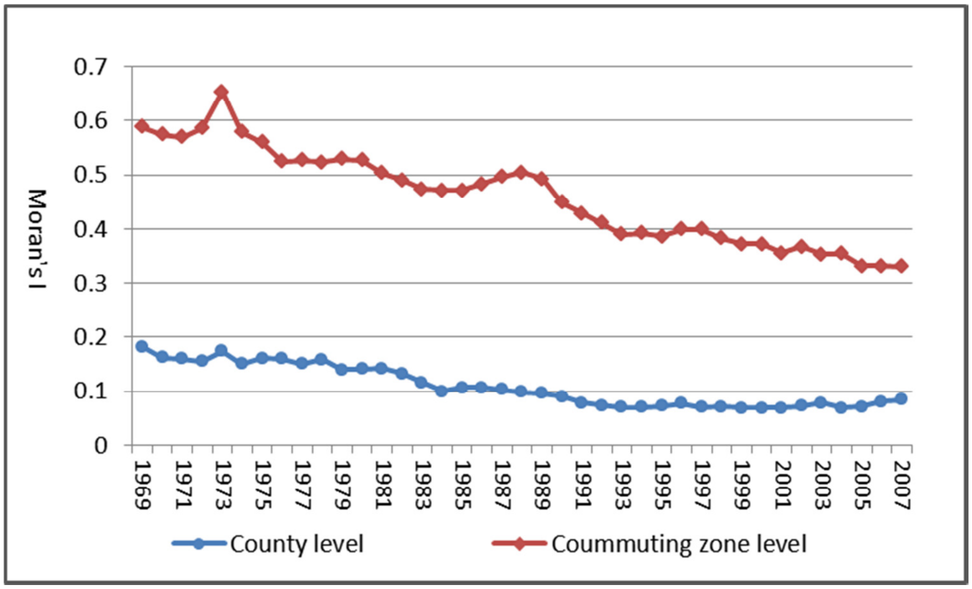


Figure 3.4. Moran's *I*, county level and commuting zone level

	Adjusted R^2	AIC	Convergence rate β* (p-value)
1973-1980	29.31%	-615.65	8.87% (0.000)
1980-1984	20.05%	-1371.34	6.78% (0.000)
1984-1990	1.29%	-1793.47	0.81% (0.001)
1990-1994	17.74%	-2298.72	3.34% (0.000)
1994-2001	0.31%	-2066.36	-0.33% (0.072)
2001-2007	-0.12%	-1864.79	-0.08% (0.712)
1973-2007	30.63%	-673.7	1.80% (0.000)

Table 5.1. Absolute β-convergence model OLS estimation

Note: * $\beta = \frac{\ln(b+1)}{-T}$, here T is the number of years in between.

	Robust LM-ERR* (*p*-value)	Robust LM-LAG** (*p*-value)	Moran's *I* Test*** (*p*-value)
1973-1980	54.127 (0.000)	9.052 (0.003)	0.526 (0.000)
1980-1984	38.170 (0.000)	4.438 (0.035)	0.480 (0.000)
1984-1990	1.479 (0.224)	0.391 (0.532)	0.411 (0.000)
1990-1994	8.547 (0.030)	10.578 (0.001)	0.356 (0.000)
1994-2001	8.226 (0.004)	4.734 (0.296)	0.266 (0.000)
2001-2007	4.024 (0.045)	3.136 (0.077)	0.431(0.000)
1973-2007	1.791(0.181)	35.522 (0.000)	0.340 (0.000)

Table 5.2. Diagnostics for Spatial Autocorrelation

Note: * Robust Lagrange Multiplier test against spatial error autocorrelation

** Robust Lagrange Multiplier test against spatial lag autocorrelation

*** Moran's *I* test for residual spatial autocorrelation

	AIC	b (p-value)	Convergence rate β	λ or ρ (p-value)*
1973-1980				
Spatial error (ML)	-1005.5	-0.352 (0.000)	6.20%	0.758(0.000)
Spatial lag (ML)	-990.91	-0.217 (0.000)	3.49%	0.705(0.000)
OLS	-615.65	-0.463 (0.000)	8.87%	
1980-1984				
Spatial error (ML)	-1689.2	-0.202 (0.000)	5.65%	0.714(0.000)
Spatial lag (ML)	-1676.9	-0.144 (0.000)	3.88%	0.672(0.000)
OLS	-1371.34	-0.238 (0.000)	6.78%	
1984-1990				
Spatial error (ML)	-2018.9	-0.032 (0.036)	0.55%	0.635(0.000)
Spatial lag (ML)	-2020	-0.028(0.020)	0.47%	0.635(0.000)
OLS	-1793.47	-0.047 (0.001)	0.81%	
1990-1994				
Spatial error (ML)	-2481	-0.097 (0.000)	2.56%	0.607(0.000)
Spatial lag (ML)	-2484.4	-0.081 (0.000)	2.11%	0.576(0.000)
OLS	-2298.72	-0.125 (0.000)	3.34%	
1994-2001				
Spatial error (ML)	-2172.8	0.042 (0.002)	-0.59%	0.509(0.000)
Spatial lag (ML)	-2168.4	0.026 (0.029)	-0.36%	0.496(0.000)
OLS	-2066.36	0.023 (0.072)	-0.33%	
2001-2007				
Spatial error (ML)	-2113	0.018 (0.158)	-0.30%	0.654(0.000)
Spatial lag (ML)	-2111.9	0.011 (0.335)	-0.18%	0.654(0.000)
OLS	-1864.79	0.005 (0.712)	-0.08%	
1973-2007				
Spatial error (ML)	-854.29	-0.286 (0.000)	0.99%	0.632(0.000)
Spatial lag (ML)	-880.31	-0.228 (0.000)	0.76%	0.598(0.000)
OLS	-673.7	-0.458 (0.000)	1.80%	

Table 5.3. Spatial Dependent Convergence Model Estimations

Note: * $\lambda$is the spatial coefficient for spatial error model, and ρ is the spatial coefficient for spatial lag model

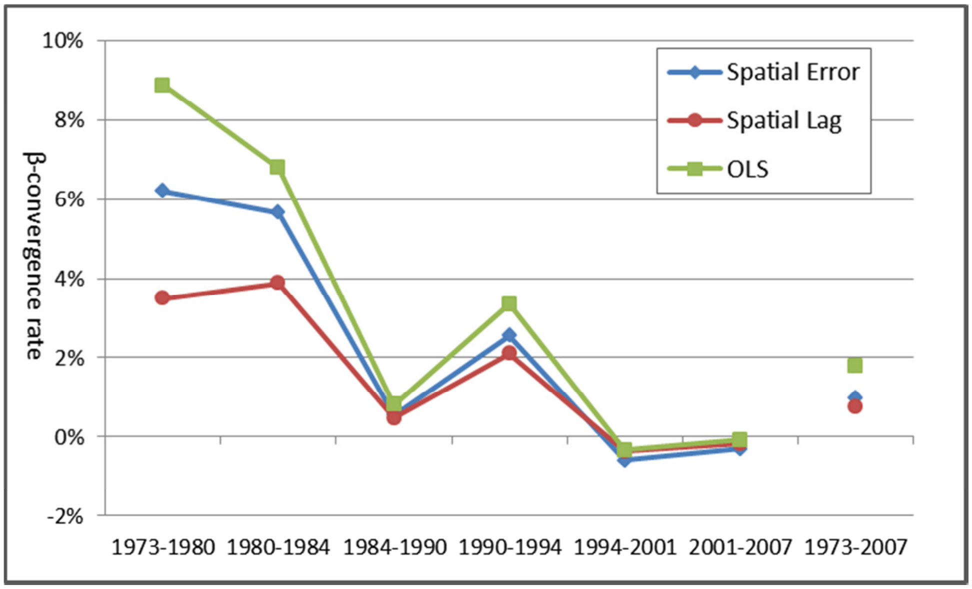


Figure 5.1. β -Convergence Rates for Three Estimations

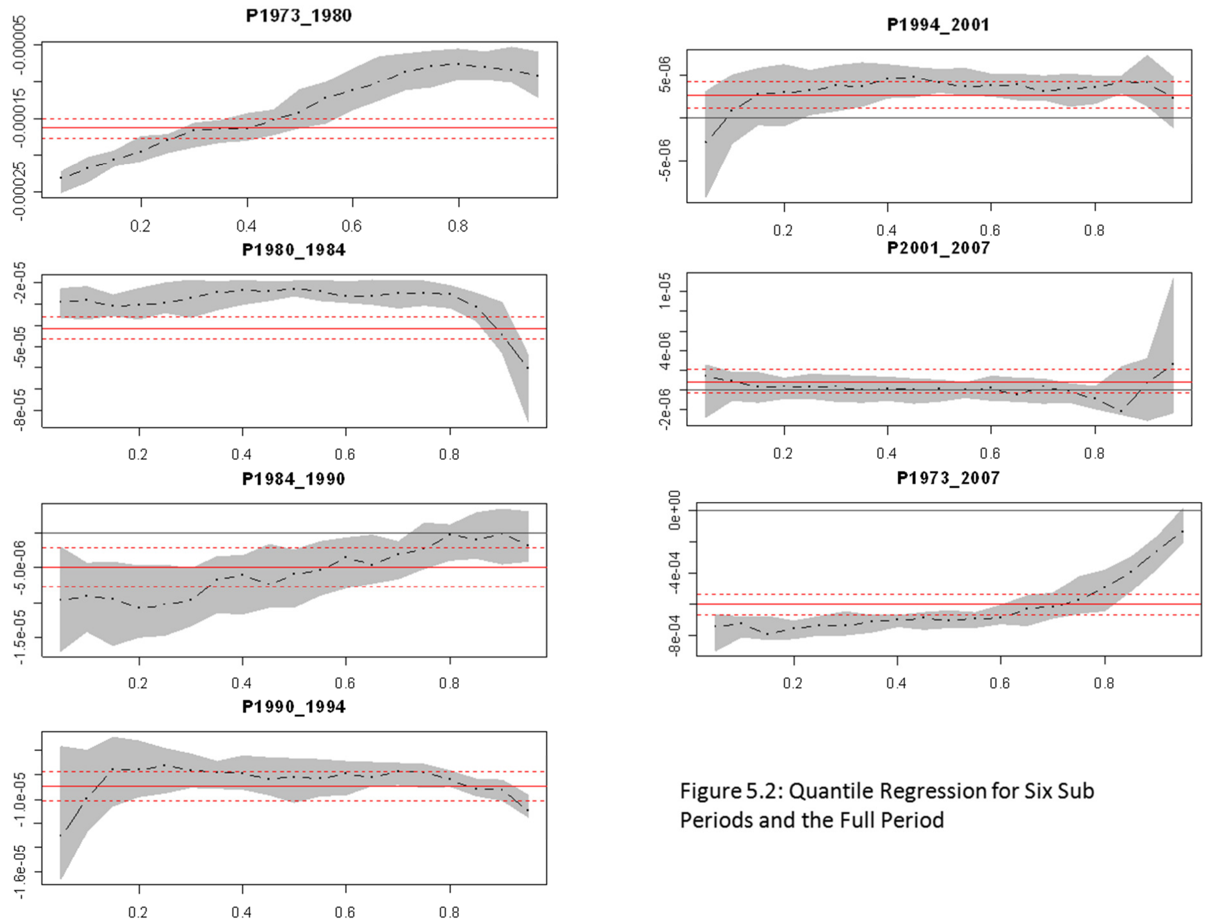


Figure 5.2: Quantile Regression for Six Sub Periods and the Full Period

Figure 5.2a. Quantile Regression for Six Sub Periods and the Full Period

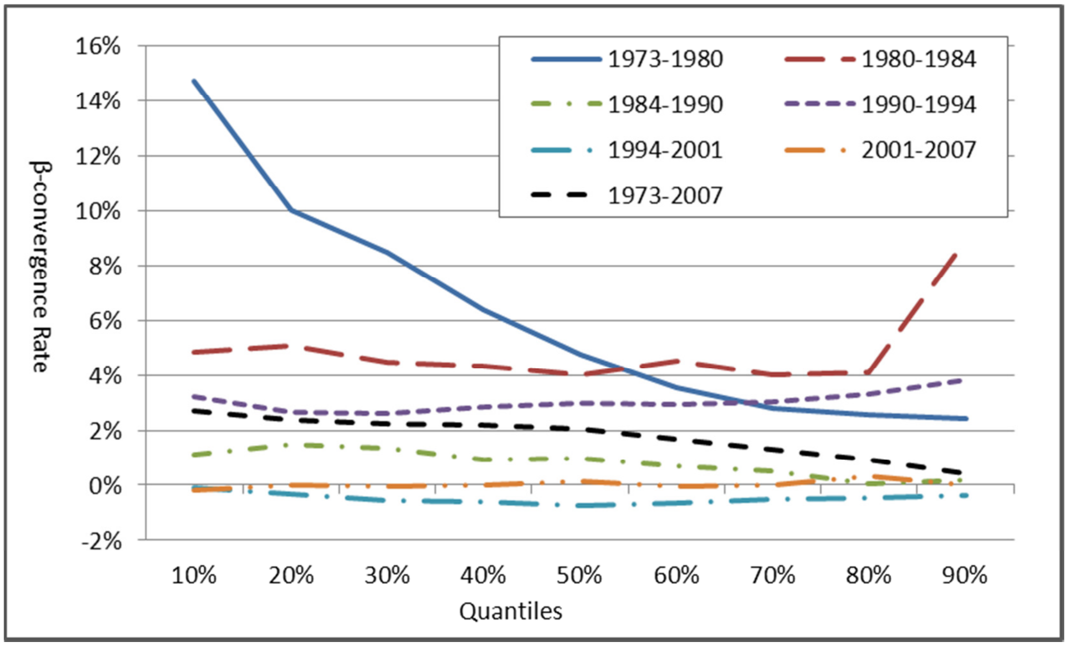


Figure 5.2*b*. β-convergence Rates from Quantile Regression for Six Sub Periods and the Full Period

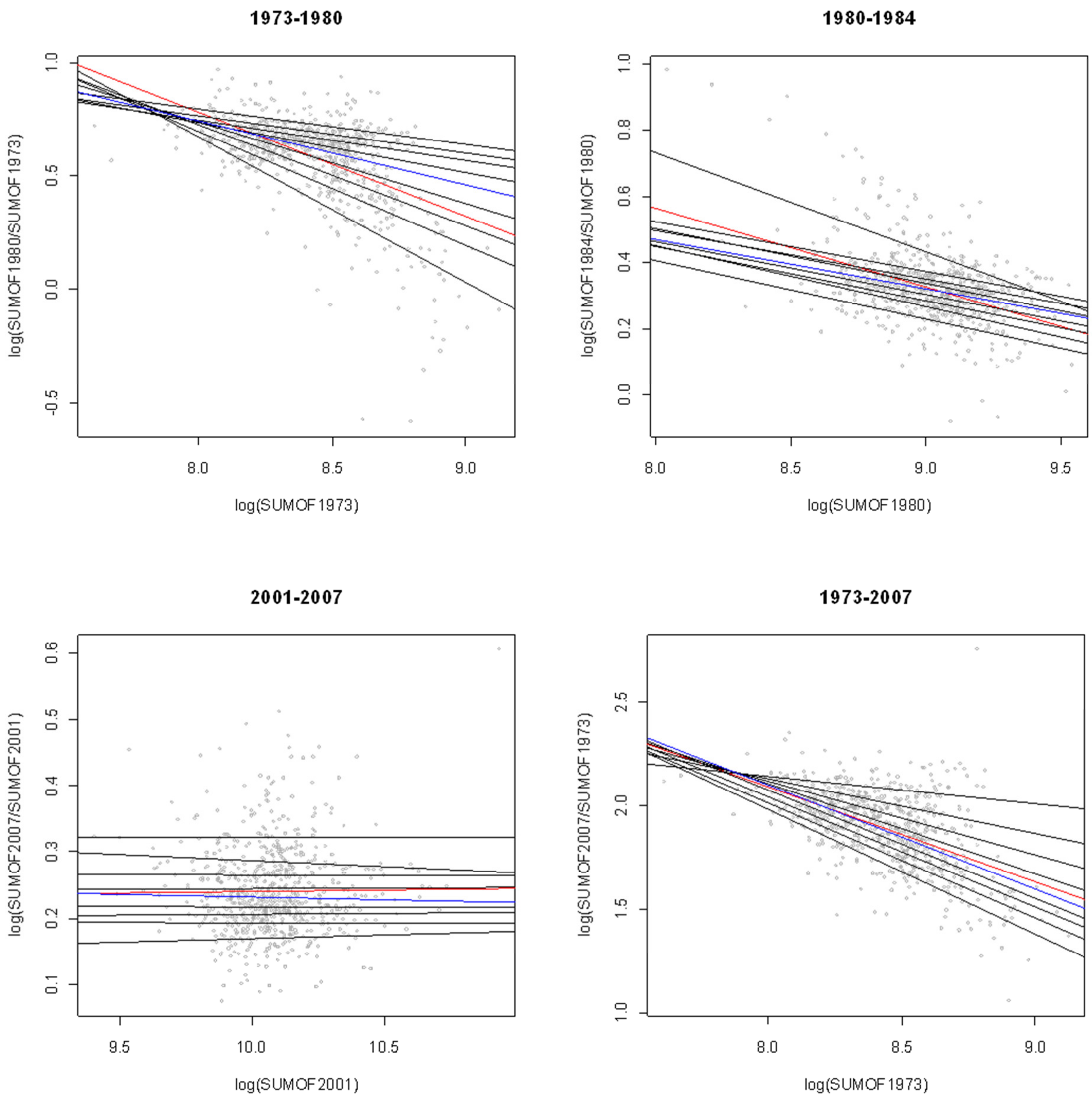


Figure 5.3. Selected Quantile Regression plots

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Appendix: LISA maps

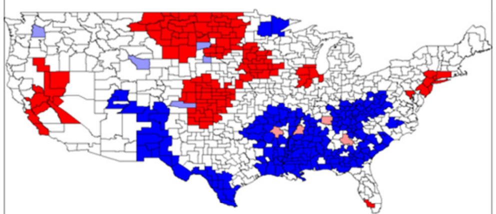
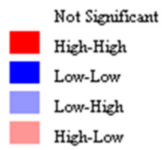


Figure A1a 1973 Per Capita Income Clusters



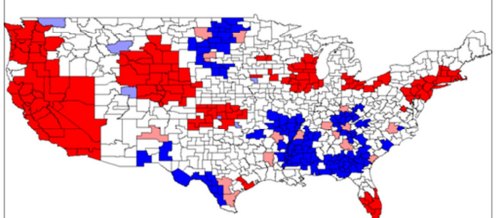


Figure A1b 1980 Per Capita Income Clusters

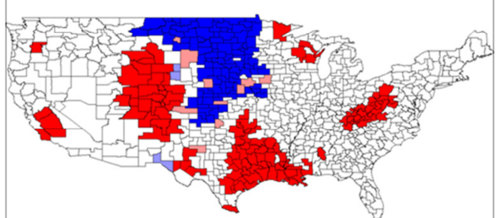


Figure A2a 1973-1980 Per Capita Income Growth Clusters

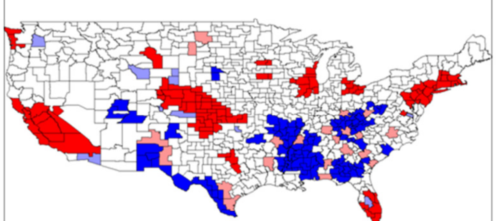


Figure A1c 1984 Per Capita Income Clusters

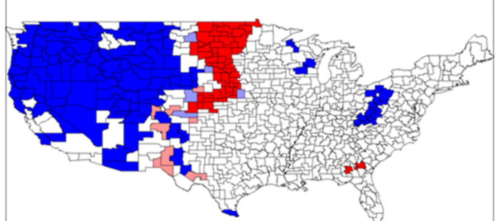


Figure A2b 1980-1984 Per Capita Income Growth Clusters

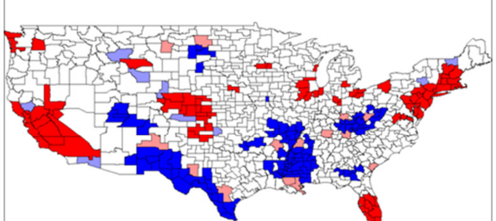


Figure A1d 1990 Per Capita Income Clusters

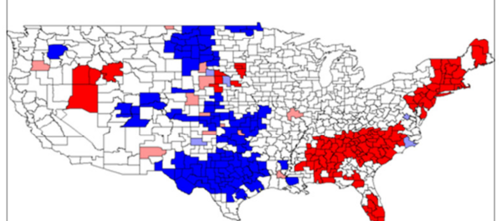


Figure A2c 1984-1990 Per Capita Income Growth Clusters

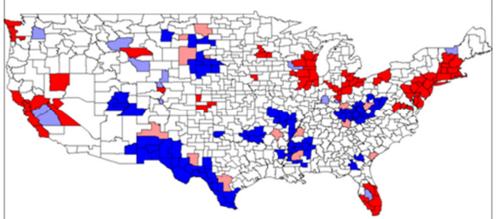


Figure A1e 1994 Per Capita Income Clusters

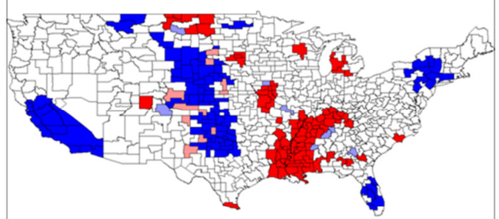


Figure A2d 1990-1994 Per Capita Income Growth Clusters

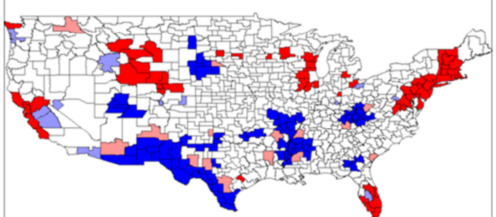


Figure A1f 2001 Per Capita Income Clusters

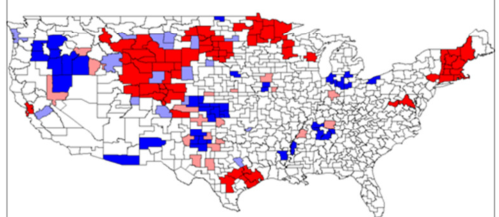


Figure A2e 1994-2001 Per Capita Income Growth Clusters

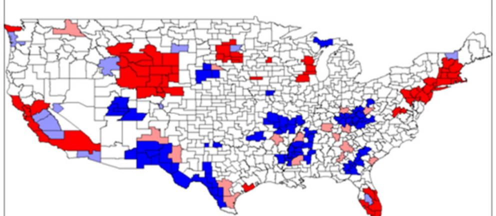


Figure A1g 2007 Per Capita Income Clusters

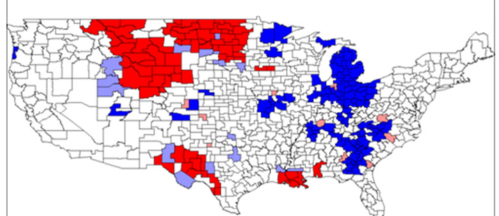


Figure A2f 2001-2007 Per Capita Income Growth Clusters

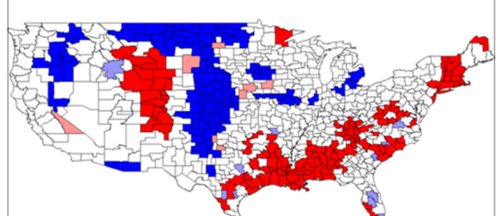


Figure A2g 1973-2007 Per Capita Income Growth Clusters