ON THE RELATIONSHIPS BETWEEN SPATIAL CLUSTERING, INEQUALITY, AND ECONOMIC GROWTH IN THE UNITED STATES : 1969-2000

Mark V. JANIKAS[*], **Sergio J. REY**[**]

***Abstract** - The literature on economic development has been divided as to the nature of the relationship between inequality and growth. Recent exploratory work in the field has provided evidence that the dynamic and spatial relationships between the two may be far more complicated than previously thought. This paper provides an spatial econometric specification for the analysis of economic growth, that allows for simultaneity as it relates to inequality. Furthermore, attention is given to the possible impacts of local clustering on the performance of individual economies in a global setting. The new methodology is applied to the US states from 1969–2000, where the counties are used for the local inequality and clustering estimates.*

Key Words : ECONOMIC GROWTH, INEQUALITY, SIMULTANEITY, SPATIAL CLUSTERING.

JEL classification : R11, R12, O15.

This research was supported by National Science Foundation Grants BCS-0602581 and BCS-0433132.

[*] Environmental Systems Research Institute (ESRI), mjanikas@esri.com

[**] Regional Analysis Laboratory (REGAL), Department of Geography, San Diego State University, and Regional Economics Application Laboratory (REAL), University of Illinois, serge@rohan.sdsu.edu

The question of how inequality is generated and how it reproduces over time has been a major concern for social scientists for more than a century. Yet the relationship between inequality and the process of economic development is far from being well understood (Philippe Aghion, 1998).

1. INTRODUCTION

What is the nature of the relationship between economic growth and inequality in a regional context? While this question has received some attention in the literature over the last decade (Perrson and Tabellini, 1994; Partridge, 1997; Forbes, 2000; Barro, 2000; Azzoni, 2001; Panizza, 2002; Janikas and Rey, 2005), a definitive answer remains elusive as differing theoretical, spatial and methodological constructs have yielded several alternative conclusions. The empirical and theoretical work on this question also tends to work at different observation scales, depending on whether the focus is on personal income distributions (microdistributions) or regional income distributions (macrodistributions). The vast majority of studies examine the effects of economic growth on personal income inequality which follows directly from the foundational work of Kuznets (1955). In large part the relationship between inequality and growth has been viewed through a recursive lens with the former being specified as either a short run adjustment in stylized neoclassical growth models (Solow, 1956; Swan, 1956) or as permanent outcomes of disequilibrium growth models (Myrdal, 1957; Kaldor, 1970).

On another front, the spatial aspects of regional economic growth and inequality have begun to attract attention by researchers in several fields of the social sciences.[1] Researchers using panel and cross-sectional growth regression have become increasingly cognizant of the implications of spatial dependence on the validity of the parameters and the inferences used for hypothesis testing (Rey and Montouri, 1999; Elhorst, 2001). Therefore, it is not surprising that spatial econometric specifications are becoming widely used in the context of regional growth processes (Le Gallo, 2003; Fingleton, 2004; Elhorst, 2005).

The analyses of space in the context of regional income inequality tend to focus on the decomposition of the latter into inter/intra regional groups. These studies discretize inequality measures such as Theil's T and the Gini coefficient into within group and across group statistics (Fan and Casetti, 1994; Azzoni, 2001). While space is at the heart of these techniques, the inferential framework is commonly viewed as though the observations are independent and identically distributed which appears to be unrealistic in many regional cases.[2]

There have also been recent calls for a tighter integration between work that has advanced theoretical models of spatial agglomeration and growth

[1] See Bode and Rey (2006); Janikas and Rey (2005) for recent overviews.

[2] Rey (2004a) provides a framework for analyzing the inherent spatial characteristic of regional inequality.

(Duranton and Puga, 2005; Combes et al., 2005) on the one hand, and the rapidly developing fields of spatial econometrics and exploratory spatial data analysis (Anselin and Raymond J. G. M. Florax, 2004). As Cheshire and Malecki (2004) and Cheshire and Duranton (2005) have pointed out, the application of spatial analysis methods has repeatedly identified evidence of strong spatial clustering in regional growth processes, yet those applications have been largely lacking a theoretical underpinning that explains such clustering. At the same time, while much progress has been made in developing theoretical growth models that incorporate stylized spatial structure, the extension of these models to capture the full richness of the spatial patterns found in regional data sets is an ongoing challenge. Moreover, the translation of what formal spatial growth models we do have into estimable econometric specifications remains largely elusive.[3]

In this paper we argue that the relationship between regional growth and regional inequality offers an important nexus for the integration of recent advances in spatial analysis with those of theory. This nexus surrounds the simultaneous nature of the relationship between inequality and growth in a spatial context which, to date, has gone largely unexamined in the literature. Our emphasis is primarily on the empirical side of the theory-empirics integration in that we offer what is one of the first applications of a new spatial econometric specification for the analysis of regional economic growth and inequality, which allows for possible simultaneous spillovers between the two phenomena.

The remainder of the paper is organized as follows. The next section provides a summary of the theoretical and empirical motivation for this study. This is followed by a description of the data and the subsequent variables used in the analysis. Section 3 presents the single equation estimation and provides justification for the simultaneous econometric specification. It also contains the results of the simultaneous analysis, which is then followed by a concluding discussion.

2. MOTIVATION

2.1. The Inverted-U

Simon Kuznets (1955) hypothesized that the relationship between economic growth and inequality follows an inverted-U progression. In the initial stage of development, inequality and growth are low as the economy and subsequent labor market are based primarily on agriculture. As industrialization begins, growth and inequality increase as a select number of the population accumulates wealth in the new sector of the economy. Finally, while economic growth continues through various economies of scale, the distribution of wealth begins to spread out as an increasing amount of labor shifts to the industrial sector leading to a decrease in overall personal income inequality.

[3] Important recent exceptions are Fingleton and López-Bazo (2006) ; Fingleton (2005).

The inverted-U hypothesis has been tested extensively in the empirical literature. The results of these analyses differ in the context of various geographical scales and in light of competing research methodologies. Kuznets's theory was initially placed in the context of international economies, where broad socio-political differences could distinguish the approximate development stage a country was in. Empirical work at the international scale initially supported the inverted-U hypothesis (Perrson and Tabellini, 1994; Perotti, 1996), however, Forbes (2000) found evidence of a positive relationship between growth and inequality and Barro (2000) noted that the relationship between the two is weak at best. The results are still unclear when the analysis is applied to a more localized setting. In the case of the United States, the evidence has indicated both a positive (Partridge, 1997) and negative (Panizza, 2002) relationship between inequality and growth. Furthermore, the outcomes do not appear to be robust to the methodological choice or the inequality measure being used in the study (Panizza, 2002).

Williamson (1965) was the first to theorize how regional inequality affected the growth performance of an encompassing economic system. He contended that regional inequality and growth also followed an inverted-U pattern related to labor/capital mobility, changes in government policy and variations in natural resources endowments. Williamson was primarily interested in the relationship between interstate inequality and the growth performance of the nation as a whole. Amos (1988) disaggregated this notion further by analyzing the relationship between interstate economic growth and intrastate inequality. His paper contended that the rural-urban differences of the counties within states were a determining factor for regional disparities *among* states.[4] In particular, Amos employed the following econometric specification to identify whether regional inequality stabilizes or increases after the implied transition:

$$I_i = \beta_0 + \beta_1 Y_i + \beta_2 Y_i^2 \tag{1}$$

where I_i is inequality *within* state i, and Y_i is per capita income for state i. Y_i^2 is the polynomial term that allows for the possible nonlinear nature of the relationship. Amos found that the process does not appear to stabilize after the inverted-U transition, rather the process follows an increase-decrease-increase pattern, where one would expect increasing levels of inequality within regional economic units of a highly developed nation.

Two important concepts can be taken from the work of Amos (1988) :

1. Interregional growth performance is an important aspect for analyzing intraregional income disparity.
2. Regional inequality is a function or outcome of regional growth.

[4] Williamson and Amos used the United States for their case studies.

The first matter relates to the internal dynamics of regional systems. This notion is embraced and extended in this paper. The latter point indirectly refers to notions of causality, as growth drives inequality. Despite the directionality implied by the Amos model, the literature on Kuznets's inverted-U can be seen as bi-directional, where inequality feeds off growth and vice-a-versa.

2.2. Economic Growth Models

While the theories and applied works related to Kuznets's inverted-U made strides towards explaining the relationship between economic growth and inequality, they are by no means exclusive. Regional growth and inequality could perhaps best be examined in light of the economic growth models based on notions of equilibrium and disequilibrium. The relationship between growth and inequality is not as tacit in these models, as notions of convergence can be easily confused with those of regional inequality. The Neoclassical growth model, initially proposed by Solow (1956) and Swan (1956), contends that regional inequality and growth should be negatively related, as factor mobility would lead to poorer regions catching up with wealthier ones. Alternative theoretical models proposed by (Myrdal, 1957) and (Kaldor, 1970), and further stylized in the field of New Economic Geography (Fujita and Krugman, 2004), contend that increasing returns to scale is the dominating force in the context of economic growth, and therefore, increasing regional inequality should be realized in an applied setting. Lastly, the models proposed in endogenous growth theory relax the strict assumptions of the Neoclassical model, which may or may not lead to decreasing levels of regional inequality (Aghion and Howitt, 1998).

In the above models, regional economic convergence and inequality are difficult to distinguish. One can view convergence as an analysis of regional disparity over time. Consider a common example where poorer regions within an economy are growing faster than wealthier ones. These regions are said to be converging because the economic gap between them are shrinking over time. Similarly, a measure of inequality taken at the same geographic scale should generally decrease over time. While regional inequality analyses tend to depict a detailed view of disparity at one point in time, the relationship with convergence is evident and often overlooked in the literature. Furthermore, unlike the inverted-U hypothesis, the actual inequality *within* the region is generally overlooked.

The empirical convergence literature on convergence is broken into two distinct categories. The first set of approaches are confirmatory in nature, where data is used to test formal economic growth theories. The vast majority of these studies are based on the work of Barro and Sala-i-Martin (1995), where the researcher analyzes the results of unconditional and conditional growth regressions to ascertain whether regional economies are converging. Citing misgiving over the theory underlying the Neoclassical approach and the empirical reality in many convergence analyses, a series of exploratory approaches for analyzing income distribution dynamics have arisen which were in large part pioneered by Quah (1993a,b, 1996b,a). Despite the wide variety of methodologies employed in the applied work on convergence, notions of regional inequality have been viewed in large part as an outcome of growth. Nevertheless, the methods and models employed in the convergence literature provides a strong backbone for analyzing regional disparities.

2.3. Regional Growth, Inequality and Space

The spatial aspects of economic growth and inequality have only recently begun to attract attention in the literature.[5] Applied work on economic growth has begun to take into account the notions of spatial dependence and heterogeneity (Rey and Montouri, 1999; Fingleton, 2001; Rey, 2001; Le Gallo, 2003; Le Gallo and Ertur, 2003; Fingleton, 2004; Le Gallo, 2004). There has be an explosion of panel data analyses for the study of convergence that primarily focus on spatial fixed effects.[6]

While the incorporation of spatial dependence in the methodologies used to analyze regional convergence is a major innovation in the empirical literature, it is generally viewed separately from the work on spatial inequality (Rey and Janikas, 2005). The spatial analysis of regional inequality tends to focus on the decomposition of inequality into global and local measures (Theil, 1996; Kanbur and Zhang, 1999). While space is at the heart of these empirical works, the methodologies often ignore the inferential pitfalls associated with spatial data.[7] Furthermore, empirical spatial inequality analyses are usually viewed in isolation from their economic growth counterparts, which have been shown to be a driving force in the disparities we observe. This leads to the research questions for this paper :

- What is the relationship between inter-state economic growth and intra-state inequality? Is it simultaneous?
- How is a state's growth performance affected by internal spatial clustering?
- Is intra-state inequality and spatial clustering related?

3. METHODOLOGY AND ANALYSIS

3.1. Data

The data on regional incomes was obtained from Bureau of Economic Analysis (BEA). The ArcView Shapefiles at the state and county levels were taken from the US Census Bureau in the 2000 formation.[8] Several variables were created from the BEA data :

---

[5] See Abreu et al. (2005); Rey and Janikas (2005) for detailed reviews of the inclusion of space in the analysis of economic change.

[6] See Elhorst (2001, 2003, 2005); Baltagi and Li (2004) for descriptions and applications of panel data models in the presence of spatial dependence.

[7] See Rey (2004b,a) for a discussion and examples of regional inequality measures that are directed at the inherent spatial aspects of cross-sectional data.

[8] Several counties divided over the time period. The authors shared the variables backwards based on proportions at the time of the split. Furthermore, the Virginia townships were aggregated as per the BEA data. See Janikas and Rey (2005) for further details.

pcr : The per capita incomes for each county and state were normalized to be relative to the national average at each time period. The actual pcr used in the regression context represents the state as a whole, which is subsequently analyzed in the context of the intrastate measures of inequality and spatial clustering.

theil : Theil's T global measure of inequality based on intrastate pcr from 1969–2000.[9]

Z : The z-value for Moran's I global measure of spatial autocorrelation based on intrastate pcr from 1969–2000.[10]

pcr simply provides a measure of relative income across the states in each time period, where a larger value is usually associated with a more prosperous economy. The measures of inequality and spatial clustering are examined at the county level, providing us with some *internal* dynamics with which to compare at an interstate level.[11]

3.2. Exploratory Analysis

We initially addressed some aspects of the research questions in a previous paper (Janikas and Rey, 2005). We used a variety of exploratory techniques to view the possible trivariate relationship between growth, inequality and spatial clustering. Using the United States as the study area, we found that inequality decreased at the interstate level, but increased within the states. There also appeared to be a positive relationship between intrastate inequality and growth. We also indicated that the spatial concentration of incomes decreased over time at both the inter-and intra-state scales of measure, signifying a possible homogenizing of regional incomes across space. Furthermore, there appeared to be a strong positive relationship between spatial clustering and inequality at the state level, but the average relationship at the county level was negative.

---

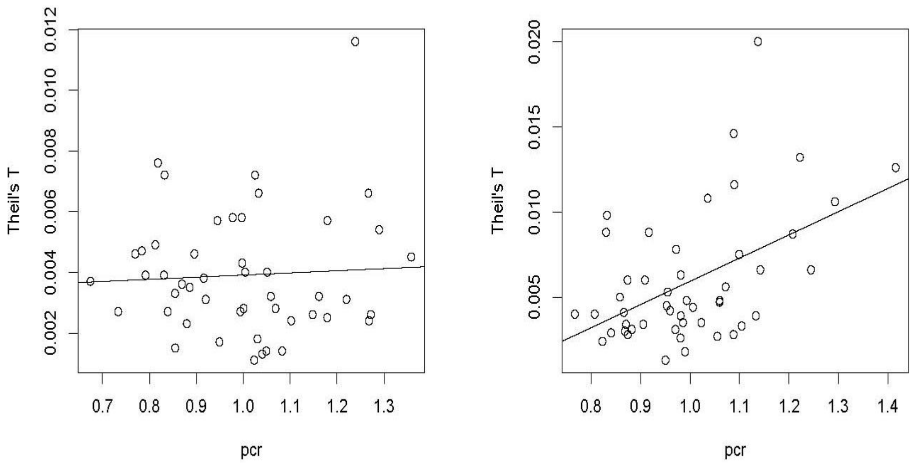
[9] The inequality measure was normalized by the number of counties in the corresponding state.

[10] We used normality as our basis of inference.

[11] All of the base variables used in this analysis were created using the Space Time Analysis of Regional Systems (STARS) geocomputational package: https://sourceforge.net/projects/stars-py. While there has been some evidence that the empirical study of the relationship between regional economic growth and inequality may not be robust to the inequality measure being employed (Panizza, 2002), the correlation between the Theil's *T* and Gini coefficients for the US states over the time period was roughly .97. Furthermore, the use of the Gini measure of inequality didn't change the significance of the results herein, therefore, we continued the analysis with the Theil's *T* measure for consistency as it relates to the previous exploratory paper (Janikas and Rey, 2005). It is also important to note that the BEA data is not adjusted based on region price differences, and as such, the measure of inequality simply represents the disparity of income within each state and is not entirely representative of social equity. The data analysis and resulting graphics portion of this paper was written in the open source statistical program R: http://www.r-project.org/.

This paper was merely a starting point for our analysis. We used it to identify some possible correlations between the variables and to generate some interesting research hypotheses. Perhaps the most important thing we noted from this analysis was that economic growth might be best related to the *change* in regional inequality rather than the *level*. This may indicate that the relationship between the two is bidirectional, with the two feeding off each other in a simultaneous fashion. Figure 1 contains the scatter plots for pcr and theil in 1969 and 2000. It is clear that there is little or no relationship between the two in 1969, but that appears to change by the end of the period. This result is central to our work and applied in the confirmatory setting.

Figure 1: Inequality and Relative Income in 1969 and 2000



3.3. A Note on Specification

The specification of a set of equations that describe the possible simultaneous relationships between growth and inequality is a bit tricky in that the economic development literature has a well justified functional form that relates changes in per capita incomes to structural variables at the initial period of study. The regional inequality literature does not enjoy the same confidence, rather researchers have tried to mimic the functional form of Kuznets' inverted-U by regressing the level of inequality at one time period on the level of income and it's square.[12] Furthermore, Barro (2000) found that personal income inequality appeared to be correlated with log of income and not the unaltered level. In this analysis we are interested in the change in regional inequality over time which appears to lend itself indirectly back to the Neoclassical Growth Model, where we would expect the change in regional inequality to be negatively correlated with the it's value at the initial time period. This is somewhat analogous to the notion of β-convergence, where factor mobility

[12] See Amos (1988) for an example in a regional context.

should lead the homogenizing of regional incomes over time.[13] With this in mind, the regional inequality regression should be viewed as somewhat of an exploratory equation where we seek to provide new insight into the possible effects of economic growth on the observed changes in regional inequality.[14]

3.4. Single Equation Analysis

The two dependent variables in our analysis are the growth rates of income and intra-state inequality given by:

$$y_1 = \ln\left(\frac{\text{pcr}_{t_{2000}}}{\text{pcr}_{t_{1969}}}\right),\ y_2 = \ln\left(\frac{\text{theil}_{t_{2000}}}{\text{theil}_{t_{1969}}}\right). \tag{2}$$

We begin with two separate equations, one for growth and the other for regional inequality:

$$y_1 = \beta_0 + \beta_1 \ln \text{pcr}_{t_0} + \beta_2 \ln \text{theil}_{t_0} + \beta_3 \text{z}_{t_0} + \varepsilon_1 \tag{3}$$

$$y_2 = \beta_0 + \beta_1 \ln \text{pcr}_{t_0} + \beta_2 \ln \text{theil}_{t_0} + \beta_3 \text{z}_{t_0} + \varepsilon_2 \tag{4}$$

where $\ln \text{pcr}_{t_0}$, $\ln \text{theil}_{t_0}$, and z_{t_0} represent regional income, inequality and spatial clustering for each state in 1969. We solved each equation separately and tested for various types of spatial effects. The results for the growth model (y_1) are presented in Table (1). The LM tests for spatial dependence indicated that a spatial lag model may be appropriate, so we compared the Ordinary Least Squares (OLS) results with those computed from the following Spatial Autoregressive (SAR) model :

$$y_1 = \beta_0 + \beta_1 \ln \text{pcr}_{t_0} + \beta_2 \ln \text{theil}_{t_0} + \beta_3 \text{z}_{t_0} + \rho_1 W y_1 + \varepsilon_1 \tag{5}$$

where ρ is the spatial autoregressive parameter and W is the spatial weights matrix based on row-standardized contiguity weights.[15]

The coefficient on the log of starting income ($\ln \text{pcr}_{t_0}$) was statistically significant which is in tune with Neoclassical theory, however, the speed of

---

[13] This relationship can also be viewed in the context of σ-convergence, where regional disparities should diminish over time. See Rey and Dev (2006) for an example of analyzing σ-convergence in the presence of spatial dependence.

[14] We use $\ln\left(\frac{\text{theil}_{t_{2000}}}{\text{theil}_{t_{1969}}}\right)$ as an approximation of the growth rate of inequality. y_2 could perhaps be best described by $\ln\left(\frac{\beta_0+\beta_1 \ln\text{pcr}_{t_T}+\beta_2 \ln\text{theil}_{t_T}+\beta_3 \text{z}_{t_T}+\varepsilon_{t_T}}{\beta_0+\beta_1 \ln\text{pcr}_{t_0}+\beta_2 \ln\text{theil}_{t_0}+\beta_3 \text{z}_{t_0}+\varepsilon_{t_0}}\right)$. This expression could be approximated using a Taylor Expansion. It is unclear whether this process would improve our analysis, but it is beyond the scope of this paper and as such, will be relegated for future research.

[15] Contiguity for island counties in several Northeast states were based on bridge connections and ferry routes. Contact Mark V. Janikas for more details.

convergence decreased by nearly half (0.01 to 0.006) when the spatial effects were included. This finding is similar to what was noted by Rey and Montouri (1999) in their analysis of the United States from 1929–1994.[16] The level of intrastate inequality (theil_{t_0})and clustering (z_{t_0}) in the initial time period had no apparent effect on the model as the coefficients were very small and the p-values were insignificant. In fact, the adjusted R^2 actually decreased when the intrastate measure of spatial clustering was included. The Akaike Information Criterion (AIC) provides further evidence that the spatial lag model is appropriate in this case as the value -144.57 is lower than the value for OLS (-131.71). Furthermore, the spatial autoregressive parameter (0.549) was large and highly significant. The Breusch-Pagan (BP) test did not identify a significant level of heteroskedasticity in the model (p-value = 0.322).

Table 1 : OLS and Spatial Model Results : y_1

Variable	Coefficient	S.D.	t-value/ z-value	p-value
Intercept (OLS)	0.054	0.095	0.574	0.569
(SAR)	0.004	0.075	0.050	0.960
$\ln \text{pcr}_{t_0}$ (OLS)	−0.264	0.051	−5.184	0.000***
(SAR)	−0.166	0.045	−3.728	0.000***
theil_{t_0} (OLS)	0.009	0.016	0.584	0.562
(SAR)	0.001	0.013	0.041	0.967
z_{t_0} (OLS)	0.000	0.002	0.076	0.940
(SAR)	−0.001	0.002	−0.400	0.689
Adj. R^2	0.342	AIC (OLS, SAR) −131.71, 144.57		
F-stat	9.146			0.000***
BP Test	3.483			0.322
LMerr	15.658			0.000***
RLMerr	0.621			0.430
LMlag	16.584			0.000***
RLMlag	1.547			0.213
ρ	0.549			0.000***

Table (2) contains the results from the regional inequality equation given by (4). The first thing to note is that the starting level of per capita income is significantly correlated with the growth of intrastate inequality in a positive manner. This would mean that a state with a higher level of income relative to the nation could expect to experience larger increases in regional disparities within their boundaries over time. This relationship did not appear to hold in the previous equation (3) as no significant relationship was found between the

---

[16] The speed of convergence was calculated as $\theta = \ln(\beta+1)/-T$, where T is the number of time periods in the study.

economic growth rate and intrastate inequality in the initial time period. The spatial diagnostics for the regional inequality equation (4) identified the error model was appropriate as the robust LM error test had a p-value of 0.057^{*}, and the corresponding autocorrelation coefficient ($\lambda = -0.566$) was negative and significant. The sign of λ in this case is important, as it signifies that the errors from the OLS equation are negatively correlated in space where high valued errors are colocated with low valued errors.

Some other interesting results fall out of this preliminary analysis of regional income inequality. First, there was a negative relationship between the growth of inequality and its level in the starting time period. Similar to the notion of σ-convergence, this points to a narrowing of the income distribution over time. Lastly, the spatial characteristic of the inequality is at least partly captured in the internal clustering variable (z_{t_0}). Here it appears that states with higher spatial concentrations of incomes in the initial time period would expect to experience decreases in regional disparity from 1969–2000.

Table 2 : OLS and Spatial Model Results: y_2

Variable	**Coefficient**	**S.D.**	t**-value/** z **-value**	p **-value**
Intercept (OLS)	−1.096	0.573	−1.913	0.062*
(SAR)	−0.651	0.447	−1.456	0.145
$\ln \mathrm{pcr}_{t_0}$ (OLS)	1.636	0.308	5.311	0.000***
(SAR)	1.764	0.214	8.235	0.000***
$\ln \mathrm{theil}_{t_0}$ (OLS)	−0.308	0.099	−3.101	0.003***
(SAR)	−0.241	0.078	−3.097	0.002***
z_{t_0} (OLS)	−0.053	0.015	−3.667	0.000***
(SAR)	−0.066	0.010	−6.506	0.000***
Adj. R^2	0.519	AIC (OLS, SAR) 40.79, 38.92		
F-stat	17.870			0.000***
BP Test	2.681			0.444
LMerr	1.603			0.206
RLMerr	3.618			0.057*
LMlag	0.002			0.959
RLMlag	2.017			0.155
λ	−0.566			0.049**

What are we to make of the single equation analysis? A common finding in a large number of regional growth and inequality analyses have identified that the spatial components of the processes need to be taken into account in order to draw consistent inferences on the underlying relationships involved.

This analysis was no different in that respect as each model was more appropriately described through SAR models. The relationship between interstate regional economic growth and intrastate inequality appears to be unidirectional subject to the starting value of its counterpart. While the initial level of intrastate inequality appears to have no bearing on the state's economic growth rate, the opposing relationship held significantly, as the growth rate of intrastate inequality was positively correlated with it's initial level of income. Despite the evidence that there may be a one-way connection between relative state incomes and intrastate regional disparity, the results are based on their initial levels rather than their respective changes. In order to capture the possible simultaneity between the two phenomena, it is necessary to assess whether economic growth (y_1) is a function of the growth of intrastate inequality (y_2) and vice-a-versa.

3.5. Simultaneous Equation Analysis

In order to construct an appropriate structural model for the set of equations it is imperative to identify whether either of the dependent variables are endogenous to the other. The following equations illustrate the possible endogeneity that may occur between growth of incomes and inequality:

$$y_1 = \beta_0 + \beta_1 \ln \mathrm{pcr}_{t_0} + \gamma_1 y_2 + \varepsilon_1, \tag{6}$$

$$y_2 = \beta_0 + \beta_1 \ln \mathrm{theil}_{t_0} + \gamma_2 y_1 + \beta_2 \mathrm{z}_{t_0} + \varepsilon_2. \tag{7}$$

Here, economic growth (6) is a function of its starting level of income and the growth of intrastate inequality. The initial level of spatial clustering (z_{t_0}) was omitted due to its poor ability to explain growth in the single equation analysis. The regional inequality equation (7) is now a function of it's starting level, the economic growth rate and the spatial clustering variable. Both models are estimated using the appropriate spatial autoregressive model.[17]

We employed the Durbin-Wu-Hausman Test for endogeneity for both equations.[18] The results of the tests are provided in Tables (3) and (4). It appears that intrastate inequality is not endogenous to regional economic growth due to the lack of significance of the coefficient for the residuals from the augmented regression ($\hat{\varepsilon}^1$ in Table (3)). This result eliminates the possibility of simultaneity in the form of multidirectional cross-equation feedback. Cross-equation simultaneity did appear in a recursive manner however, as the residuals from the augmented regression ($\hat{\varepsilon}^1$) in Table (4) were highly significant (p-value = 0.000^{***}).

[17] While the single equation analysis for inequality identified that the spatial error model was the correct specification, when economic growth (y_1) replaced the initial level of income ($\ln \mathrm{pcr}_{t_0}$) the spatial lag model was deemed appropriate based on the LM spatial diagnostic tests.

[18] It should be noted that the finite distance properties of this test in the presence of spatial dependence is unknown.

Table 3 : Durbin-Wu-Hausman Test for Endogeneity: y_1

Variable	Coefficient	S.D.	t-value	p-value
Intercept	0.007	0.015	0.451	0.654
$\ln \text{pcr}_{t_0}$	−0.238	0.075	−3.164	0.002***
y_2	−0.015	0.032	−0.471	0.640
$\hat{\varepsilon}^1$	0.031	0.043	0.719	0.476
Adj. R^2	0.345			
F-stat	9.246			0.000***

1 Residuals from the augmented regression.

Table 4: Durbin-Wu-Hausman Test for Endogeneity: y_2^{α}

Variable	Coefficient	S.D.	t-value	p-value
Intercept	−0.785	0.396	−1.980	0.0548*
y_1	−2.497	0.495	−5.046	0.000***
$\ln \text{theil}_{t_0}$	−0.256	0.069	−3.728	0.000***
z	−0.059	0.010	−5.890	0.000***
$\hat{\varepsilon}^2$	1.083	0.113	9.606	0.000***
Adj. R^2	0.772			
F-stat	40.840			0.000***

1 Residuals from the augmented regression.
α LM tests indicated the Spatial Lag model.

Based on the tests for endogeneity we constructed a set of equations where the growth of intrastate inequality is endogenously determined by interstate income growth but not in a reverse fashion:

$$y_1 = \beta_0 + \beta_1 \ln \text{pcr}_{t_0} + \rho_1 W y_1 + \varepsilon_1 \tag{8}$$

$$y_2 = \alpha_0 + \alpha_1 \ln \text{theil}_{t_0} + \alpha_2 \text{z}_{t_0} + \rho_2 W y_2 + \gamma_{12} y_1 + \varepsilon_2 \tag{9}$$

where $\gamma_{12} y_1$ represents the possible recursive interaction between regional inequality and growth. Solving this set of equations is not a simple matter. We have several forms of simultaneity present that need to be taken into account in order to identify the coefficients. We turn to the work of Rey and Boarnet (2004) in order to solve this system. The authors derived a taxonomy and methodology for solving systems of equations with spatial and cross-equation simultaneity. They employed Monte Carlo methods to analyze the properties of several estimators in the presence of multidimensional simultaneity. Based on an assessment of the estimators Root Mean Squared Error (RMSE), Rey and Boarnet found that the Instrumental Variable (IV) models fashioned by

Kelejian-Robinson-Prucha (KRP) performed the best. Therefore, we employed two versions of the KRP flavored models to jointly determine the system.

This set of equations is identified as model #23 in Rey and Boarnet's taxonomy, that is, it is recursive with two spatial lags. The first of the two estimators for the regional inequality equation is given by :

$$\hat{\theta}_{\mathrm{KRP}_1} = \left(Z_2' Z_2\right)^{-1} Z_2' y_2 \tag{10}$$

where,

$$Z_2 = \left\lfloor x_2,\, \hat{y}_1,\, \hat{W}y_2 \right\rfloor \tag{11}$$

$$\hat{y}_1 = Qy_1 \tag{12}$$

$$Q = X\left(X'\ X\right)^{-1} X' \tag{13}$$

$$X = \left[x_2,\, x_1,\, W\breve{X}\right] \tag{14}$$

$$\hat{W}y_2 = QWy_2 \tag{15}$$

$$\breve{X} = \left[x_2,\, x_1\right] \forall\, j \neq \textbf{constant} \tag{16}$$

The second KRP estimator ($\hat{\theta}_{\mathrm{KRP}_2}$) is solved in the same manner but it includes a higher order cross-regressive lag variable $WW\breve{X}$, which is added to the matrix X previously given in (14). One can use the same IV estimation procedure to solve for y_1 with the equation interaction term (in this case $\hat{y}_2$) excluded from the design matrix :

$$Z_1 = \left\lfloor x_1\, \hat{W}y_1 \right\rfloor \tag{17}$$

For this analysis the variance-covariance matrix was constructed using an extension of the Eiker-Huber-White "sandwich" method which is robust to clustered error terms (Baum et al., 2002).

Table (5) contains the results for the simultaneous KRP models and provides it in the context of the single equation SAR models. As expected, all of the coefficients for the economic growth equation were similar, as there was no feedback from the inequality expression. The coefficients related to the log of staring income were significantly negative at the 1% confidence interval across all of the models, indicating unconditional $\beta-$convergence among the US states over the time period. Again, it is worth mentioning that the inclusion of the spatial effects decreased the speed of convergence relative to the OLS results in the single equation analysis. This result is consistent in the simultaneous framework was well, as the speed of convergence corresponding to the OLS equation ($\theta = 0.01$) was nearly twice as fast as the results for the $\mathrm{KRP}_{1,2}$ models ($\theta = 0.006,\ \ 0.006$).

Table 5 : Spatial Simultaneous and Single Equation Results

Variable/Model	y_1			y_2		
	Coefficient		p **-value**	**Coefficient**		p **-value**
Intercept						
SAR	−0.003		0.652	−1.085		0.088*
KRP_1	−0.003		0.652	−0.774		0.365
KRP_2	−0.003		0.654	−0.897		0.224
$\ln \text{pcr}_{t_0}$						
SAR	−0.167		0.000***			
KRP_1	−0.162		0.008***			
KRP_2	−0.163		0.008***			
$\ln \text{theil}_{t_0}$						
SAR				−0.269		0.016**
KRP_1				−0.241		0.098*
KRP_2				−0.232		0.062*
z_{t_0}						
SAR				−0.036		0.029**
KRP_1				−0.047		0.106
KRP_2				−0.033		0.184
Y_1						
SAR				−1.418		0.088*
KRP_1				−5.883		0.070*
KRP_2				−3.949		0.125
ρ						
SAR	0.544		0.000***	0.307		0.086*
KRP_1	0.569		0.049**	0.089		0.839
KRP_2	0.567		0.051*	0.355		0.346

Another important thing to note is that the standard error for all the variables increased in the simultaneous framework. This indicates that the simultaneous estimation of the system of spatial equations is less efficient than the single equation estimates in its current methodological form. This is particularly apparent for the spatial autoregressive term where the estimates of ρ remained almost constant across the models but the p -values jumped from 0.000^{***} to 0.049^{**} in the KRP_1 model and 0.051^{*} in the KRP_2 model. It is clear that the estimator for the variance-covariance matrix may not be robust to the cross-equation and spatial simultaneity present in this system of equations, which is a methodological issue further discussed in the conclusions.

Shifting our attention to the inequality regression, we found that there was a significant negative relationship between the growth of inequality and the endogenous growth of income in the KRP_1 model but not for KRP_2.

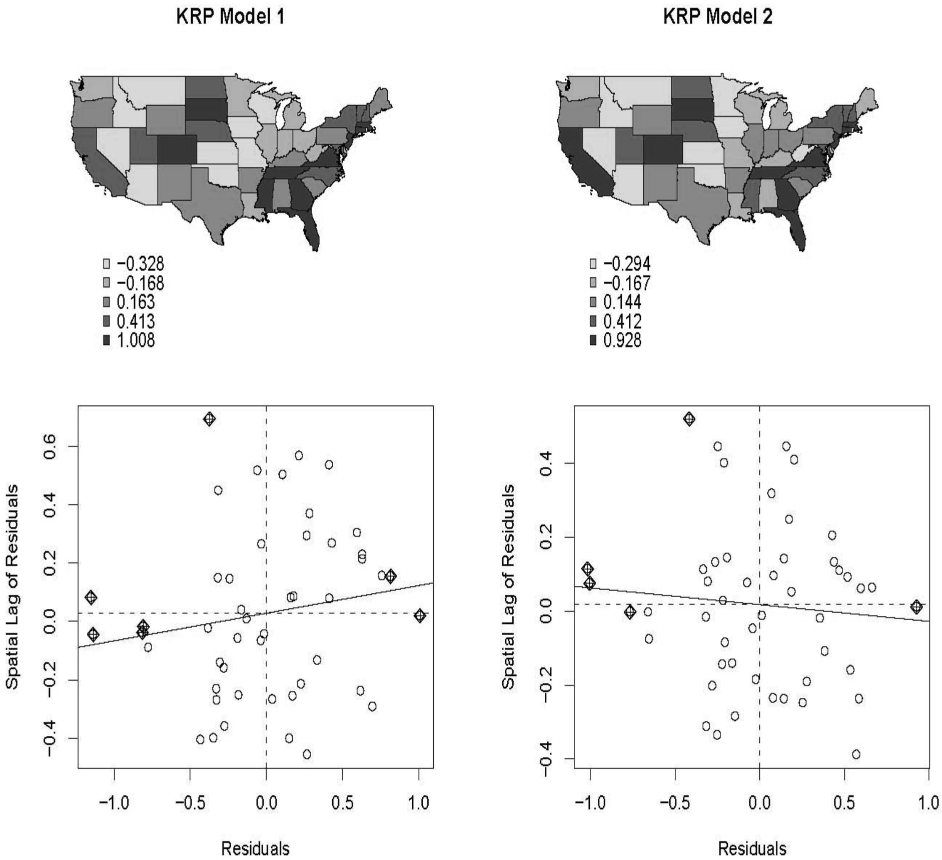
This may allude to the importance of the omitted variables in the economic growth expression on the change in inequality. What is perhaps most surprising is that the relationship between the growth of inequality and the *starting* level of pcr was positive which is in discordance with the result here. This lack of consistency has been noted in the literature subject to changing empirical methodologies and the inequality measures being used (Panizza, 2002). Furthermore, this result provides further motivation for an improved theoretical perspective on the relationship between regional growth and inequality, specifically as it relates to the identification of whether *levels* or *changes* should be compared.

The significance of the internal spatial clustering variable dissipated in the simultaneous framework, as the p-value dropped from 0.029^{**} to 0.106 in the KRP_1 model and 0.184 KRP_2 model. At first glance it could be assumed that the conditional affect associated with the simultaneous interaction with the growth equation attributed to this change in significance, however, the coefficients for z_{t_0} were relatively similar across the three models (SAR = -0.036, KRP_1 = -0.047, KRP_2 = -0.033). This points to the apparent efficiency problems associated with the variance-covariance matrix implemented. Taking this aspect into consideration it seems apparent that states that have higher levels of spatial clustering in the initial period can expect to have smaller growth rates of inequality.

The autoregressive parameter in both the KRP_1 and KRP_2 models for the inequality regression were not significant, which stands in stark contrast to the single equation model where the value of $\rho = 0.307$ had a p-value of 0.086^{*}. This may signify that the autocorrelation in the simultaneous system is largely found in the economic growth equation. It was also noted in the single equation analysis that an LM test pertaining to the inequality regression (6) indicated the spatial error model was appropriate. These results taken in unison appear to bolster the recursive nature of the set of equations, as a portion of the error in the stand-alone inequality equation may reflect the omitted economic growth rate (Y_1) which has been shown to be autocorrelated in space.

In order to be sure that are inferences were appropriate we mapped and plotted the residuals from the inequality regression for both the KRP_1 and KRP_2 models. Figure 2 contains these results. The Moran's I test for residual autocorrelation were $\mathrm{KRP}_1 = 0.0948$ and $\mathrm{KRP}_2 = -0.0451$, resulting in p-values of 0.117 and 0.596 respectively.[19] Although neither of these values were statistically significant, KRP_1 appears to have some residual autocorrelation remaining.

Figure 2 : Morans I Results for the Inequality Equation



4. CONCLUSIONS

The theories and methods used to analyze the relationship between economic growth and inequality are contentious in many respects. One of the major issues is related to the unit of measure, as it seems clear that alternative theoretical constructs need to be incorporated when one is addressing personal rather than regional income inequality. The latter has an inherent spatial aspect,

[19] IA, KS, MT, NJ, NV, RI, and VA are significant outliers (◊) in the Moran scatter plot for the KRP_1 model. The number of outliers drops from seven to five in the KRP_2 model leaving only KS, MT, NJ, NV, and RI.

which has not received as much attention in the literature compared to its economic growth counterparts (Rey and Janikas, 2005). Furthermore, the theoretical framework surrounding the regional inequality literature does not directly relate to a defined functional form in a regression context. Lastly, there is not a great deal of empirical evidence as to the direction of the relationship between regional economic growth and inequality.

This paper attempted to address many of the issues at hand. A spatial framework was presented that allowed for the simultaneous interaction between regional growth and inequality. We found evidence for inequality being a partial function of economic growth, but not vice-a-versa. The single equation analysis indicated that states with higher per capita income levels in the starting period could expect to have larger growth rates of inequality. This result seems in tune with the theories of disequilibrium that stress the importance of cumulative causation and resulting growth poles. We then analyzed how the changes in intrastate inequality and interstate growth were related. Our result provides evidence that economic growth drives intrastate inequality. As such growth may be endogenous function in the determination of regional inequality, and would therefore need to be accounted for in the analysis of regional inequality. Furthermore, the relationship appears to be negative in the simultaneous framework which bolsters the Neoclassical theory.

Intra-state spatial clustering had no effect on growth, but appeared to be negatively correlated with intra-state inequality. This result indicates that states with high initial levels of spatial clustering will have lower growth rates on inequality. This appears to be in tune with the Neoclassical theory on economic growth, where states with higher spatial concentrations of income can expect to experience a “catching up” of poorer counties over time due to factor mobility. Lastly, similar to the work by Rey and Montouri (1999) our spatial framework identifies a slower rate of convergence when spatial dependence is taken into account. This reiterates the importance of incorporating spatial dependence when one is drawing inferences on the analysis of regional economic change.

The results from this paper clearly highlight the discrepancies in the analysis of regional economic growth and inequality. As such, we find several interesting avenues for future research. First, it was evident that the estimator of the variance-covariance matrix did not have the efficient properties desired, and therefore we propose to examine several different estimators that improve our inferential perspective. One possibility is the Heteroskedastic and Autocorrelated Variance Covariance (HAC) matrix method proposed by Kelejian and Prucha (2006). Second, we also noted that our relatively simple model excludes several important structural variables often employed in the analysis of convergence and inequality. We would therefore like to extend the model to include these variables to lessen the possible omitted variable bias in the model. Third, it would also be interesting to examine the relationship between inequality and growth at other spatial scales and across other economic systems in order to identify the robustness of the results. Next, our research methodology is based on information obtained in two distinct time periods, and perhaps a spatial panel methodology (Elhorst, 2005) could provide a more dynamic view of the relationship between regional growth and inequality. Further, our model could also allow for spatial heterogeneity to identify how regimes might play a role in the evolution of regional incomes. Lastly, our research represents an empirical approach to analyzing the relationship between regional economic growth and inequality, and further attention should be given to linking the various theoretical frameworks related to regional economic change.

REFERENCES

Abreu M., Groot H. D., Florax R., 2005. Space and growth: a survey of empirical evidence and methods. *Région et Développement*, 21, 13-43.

Aghion P., 1998. Inequality and economic growth. In Aghion, P. and Williamson, J. G., editors, *Growth, Inequality and Globalization.* Cambridge.

Aghion P., Howitt P., 1998. *Endogenous Growth Theory*. MIT Press, Cambridge.

Amos Jr. O., 1988. Unbalanced regional growth and regional income inequality in the latter stages of development. *Regional Science and Urban Economics*, 18, 549-566.

Anselin L., Florax R., Rey S. J., 2004. *Advances in Spatial Econometrics.* Springer Verlag, New York.

Azzoni C. R., 2001. Economic growth and income inequality in Brazil. *Annals of Regional Science*, 35(1), 133-152.

Baltagi, B. H. and Li, D., 2004. Prediction in the panel data model with spatial correlation. In Anselin, L., Florax, R., Rey, S. J., editors, *Advances in Spatial Econometrics.* Springer-Verlag, Berlin.

Barro R., Sala-i-Martin X., 1995. *Economic Growth.* McGraw Hill, Boston.

Barro R. J., 2000. Inequality and growth in a panel of countries. *Journal of Economic Growth*, 5, 5-32.

Baum C. F., Schaffer M. E., Stillman, S., 2002. Instrumental variables and GMM: Estimation and testing. Boston College Economics Working Paper 545.

Bode E., Rey S. J., 2006. The spatial dimensions of economic growth and convergence, *Papers in Regional Science*, 85(2), 171-176.

Cheshire P., Duranton G., 2005. Introduction. In Cheshire, P. and Duranton, G., editors, *Recent Developments in Urban and Regional Economics.* Edward Elgar.

Cheshire P. C., Malecki E. J., 2004. Growth, development and innovation: A look backward and forward. *Papers in Regional Science*, 83(1), 249-268.

Combes P. P., Duranton G., Overman H. G., 2005. Agglomeration and the adjustment of the spatial economy. *Papers in Regional Science*, 84, 314-349.

Duranton G., Puga D., 2005. Micro-foundations of urban agglomeration economies. In Henderson, J. V., Thisse, J. F., editors, *Handbook of Regional and Urban Economics,* 2063-2117. Elsevier.

Elhorst J. P., 2001. Dynamic models in space and time. *Geographical Analysis,* 33, 119-140.

Elhorst J. P., 2003. Specification and estimation of spatial panel data models. *International Regional Science Review,* 26 : 244–268.

Elhorst J. P., 2005. Models for dynamic panels in space and time : An application to regional employment in the E.U. In *Paper presented at the 52nd Annual Meetings of the Regional Science Association International, Las Vegas, NV*

Fan C. C., Casetti E., 1994. The spatial and temporal dynamics of US regional income inequality, 1950-1989. *Annals of Regional Science,* 28, 177-196.

Fingleton B., 2001. Equilibrium and economic growth: spatial econometric models and simulations. *Journal of Regional Science,* 41, 117-147.

Fingleton B., 2004. Regional economic growth and convergence: insights from a spatial econometric perspective. In Anselin L., Florax R., Rey S. J., editors, *Advances in Spatial Econometrics.* Springer-Verlag, Berlin.

Fingleton B., 2005. Beyond neoclassical orthodoxy: A view based on the new economic geography and UK regional wage data. *Papers in Regional Science,* 84, 351-375.

Fingleton B., López-Bazo E., 2006. Empirical growth models with spatial effects. *Papers in Regional Science,* 85(2), 177-198.

Forbes K. J., 2000. A reassessment of the relationship between inequality and growth. *The American Economic Review*, 90(4), 869-887.

Fujita M., Krugman P., 2004. The new economic geography: Past present and the future. *Papers in Regional Science*, 83(1), 139-164.

Janikas M. V., Rey S. J., 2005. Spatial clustering, inequality and income convergence in the U.S.: 1969-2001. *Région et Dévelopment,* 21, 45-64.

Kaldor N., 1970. The case for regional policies. *Scottish Journal of Political Economy,* 27(2), 337-348.

Kanbur R., Zhang X., 1999. Which regional inequality? The evolution of rural-urban and inland-coastal inequality in China, 1983-1995. *Journal of Comparative Economics*, 27, 686-701.

Kelejian H. H., Prucha I. R., 2006. HAC estimation in a spatial framework. *Journal of Econometrics,* Forthcoming.

Kuznets S., 1955. Economic growth and income equality. *American Economic Review,* 45, 1-28.

Le Gallo J., 2003. A spatial econometric analysis of convergence across European regions, 1980-1995. In Fingleton B., editor, *European Regional Growth.* Springer-Verlag, Berlin.

Le Gallo J., 2004. Space-time analysis of GDP disparities across European regions: a Markov chains approach. *International Regional Science Review,* 27(2), 138-163.

Le Gallo J., Ertur C., 2003. Exploratory spatial data analysis of the distribution of regional per capita GDP in Europe, 1980-1995. *Papers in Regional Science,* 82, 175-201.

Myrdal G., 1957. *Economic Theory and Underdeveloped Regions.* Duckworth, London.

Panizza U., 2002. Income inequality and economic growth: Evidence from American data. *Journal of Economic Growth,* 7, 25-41.

Partridge M. D., 1997. Is inequality harmful for growth? Comment. *The American Economic Review,* 87(5), 1019-1032.

Perotti R., 1996. Growth, income distribution and democracy: What the data say. *Journal of Economic Growth,* 1, 149-187.

Perrson T. and Tabellini G., 1994. Is inequality harmful for growth? *The American Economic Review,* 84(3), 600-621.

Quah D. T., 1993a. Empirical cross-section dynamics in economic growth. *European Economic Review,* 37, 426-434.

Quah D. T., 1993b. Galton’s fallacy and tests of the convergence hypothesis. *Scandinavian Journal of Economics,* 95, 427-443.

Quah D. T., 1996a. Convergence empirics across economies with, some, capital mobility. *Journal of Economic Growth,* 1, 95-124.

Quah D. T., 1996b. Regional convergence clusters across Europe. *European Economic Review,* 40, 951-958.

Rey S. J., 2001. Spatial empirics for economic growth and convergence. *Geographical Analysis,* 33(3), 195-214.

Rey S. J., 2004a. Spatial analysis of regional income inequality. In Goodchild M. and Janelle D., editors, *Spatially Integrated Social Science: Examples in Best Practice,* 280-299. Oxford University Press, Oxford.

Rey S. J., 2004b. Spatial dependence in the evolution of regional income distributions. In Getis A., Múr J., and Zoeller H., editors, *Spatial econometrics and spatial statistics.* Palgrave, Hampshire.

Rey S. J., Boarnet M. G., 2004. A taxonomy of spatial econometric models for systems of simultaneous equations. In Anselin L., Florax R., and Rey S. J., editors, *New Advances in Spatial Econometrics.* Springer Verlag, Berlin.

Rey S. J., Dev, B., 2006. σ-convergence in the presence of spatial effects. *Papers in Regional Science,* 85(2), 217-234.

Rey S. J., Janikas M. V., 2005. Regional convergence, inequality and space. *Journal of Economic Geography*, 5(2), 155-176.

Rey S. J., Montouri B. D., 1999. U.S. regional income convergence: A spatial econometric perspective. *Regional Studies*, 33, 143-156.

Solow R., 1956. A contribution to the theory of economic growth. *Quarterly Journal of Economics*, 70, 65-94.

Swan T. W., 1956. Economic growth and capital accumulation. *Economic Record*, 32(44), 334-361.

Theil H., 1996. *Studies in Global Econometrics.* Kluwer Academic Publishers, Dordrecht.

Williamson J., 1965. Regional inequality and the process of national development. *Economic Development and Cultural Change*, 4, 3-47.

LES RELATIONS ENTRE CROISSANCE ÉCONOMIQUE ET DISPARITÉS DE REVENU INTRA ET INTER-RÉGIONALES AUX ÉTATS-UNIS (1969-2000)

Résumé - *Certaines études récentes mettent en évidence le fait que l'introduction d'une dimension spatiale dans la relation entre croissance et inégalité de revenu conduit à rendre plus complexe les interprétations jusque là données. Un modèle économétrique est proposé dans cette perspective, appliqué au niveau communal aux États-Unis entre 1969 et 2000. Une attention particulière est accordée aux phénomènes de concentration spatiale ainsi qu'aux effets de voisinage en matière d'inégalités.*