THE EFFECTS OF SPACE AND SCALE ON BETA CONVERGENCE TESTING IN THE UNITED STATES, 1970-2004

by

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ABSTRACT

RYAN DOUGLAS JAMES. The effects of space and scale on beta convergence testing in the United States, 1970-2004. (Under the direction of DR. HARRISON CAMPBELL)

Convergence theory stems from neo-classical growth theory and hypothesizes that regional incomes will converge over time. Beta convergence, the idea that regions of initial poverty will grow faster than regions of initial wealth, has received a great deal of study and yields mixed results. Typically beta convergence is tested in an OLS regression with income changed regressed against initial income levels. From the geographic perspective, possible reasons for mixed convergence test results are the impacts that aggregation size and spatial effects can have on model performance. Interestingly, the potential impacts of these problems are relatively unexplored in the convergence literature. This dissertation fills that void through an examination of convergence in the United States from 1970-2004 at three levels of aggregations: states, Economic Areas, and counties. First an Exploratory Spatial Data Analysis is conducted in order to determine the magnitude and extent of spatial dependence in the convergence variables. Next, OLS, first order, and second order spatial models are run testing for unconditional and conditional convergence. Results indicate that spatial dependence is a problem in convergence models at all scales, and a spatial model must be used. First order spatial models out- perform second order spatial models. Regression results indicate convergence evidence to be strongest at the smaller levels of aggregation, though model fit tends to be better at larger levels. In the end, the functional Economic Area geography proves to be the most stable unit of aggregation for convergence analysis.

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CHAPTER 1: INTRODUCTION

A central concept in economic geography is that resources and wealth are not evenly distributed across the world. While the early history of modern geography simply made an effort to locate and catalogue the locations of these resources and wealth, modern systematic geography has made a larger effort to explain why those resources and wealth are distributed as they are, how they change, and how they interact. Central to this more systematic approach to economic geography is the inquiry and modeling of why regions grow. At the broadest level, three competing theoretical frameworks can be used to explain economic structure, and in turn regional growth; Exogenous (neo-classical) Growth Theory, Endogenous Growth Theory, and Growth Pole Theory. While these approaches have unique and intuitive factors that differentiate the forces driving growth, there is a commonality amongst them. Each recognizes a regional inequality of wealth; that investment is free to move across regions; that firms will invest where returns are highest; and that investment plays a central role in determining regional growth.

The neo-classical exogenous model comes out of the Harrod-Domar and Cobb-Douglas lines of regional production functions (Maliza and Feser 1999). The framework builds upon Solow (1956), who first presented a growth model where the production of the region is dependent on its capital investment, labor, savings, and an exogenous technological factor. The key factors of this growth framework are its diminishing returns to investment and assumed exogenous technological change (Romer1990). These factors work together to produce aggregate regional output and growth, but the key factor that sparks a change in the regional production function is a change in the technological paradigm. In these models, technological change is assumed to occur externally to the firm and region. Under the assumed diminishing returns to investment and ubiquitous technological availability, investment will move from more wealthy regions to developing regions leading to a natural cycle of regional investment and disinvestment, and a larger process of filtering down of investment (Park and Wheeler 1983). This natural pattern is a bit disconcerting for policy makers, since it implies that little can be done to spur regional growth or even keep investment within a region (Shaw 1994).

In response to that externally driven growth process, a competing set of theories operate under the assumption that there are policy mechanisms that can be utilized to alter regional production functions, giving them a competitive advantage in the race to attract growth. That is, growth can come from an endogenous factor. The production function in these endogenous models comes from the neo-classical models. However, it is different in that the technological component can be modified. This is typically captured through the addition of variables to account for investment in the stocks that can influence the cost of doing business in a region (Arrow 1962; Romer 1990; Shaw 1994). Endogenous Growth Theory and its policy derivatives attempt to directly change one component of a region's production function. In many cases, these policies seek to change the technological aspect, or find other manners in which returns to investment and labor can be kept high (Pack 1994). Some of these alterations include investment in the production, attraction, and retention of the human capital that produces technological changes (Romer 1990, Florida 1999) or tax incentives that can drive investment in capital and labor (King and Rebolo 1990, Shaw 1994). Stern (1991) also notes the importance of infrastructure provision and sectoral transfer in developing economies. The investment in these factors is theorized to produce an innovative region which will adopt the new production function before other competing regions. In theory, this will keep the production function from reaching a steady state and keep growth occurring in a region.

Outside of the growth theories expressed through the modeling of a production function, another growth theory operates under a similar set of assumptions as Endogenous Growth Theory. Growth Pole Theory, and its policy spin-off Growth Centers, also theorize that a region can manipulate its growth trajectory. The theoretical base behind Growth Pole and Growth Center Theories comes from Core-Periphery Models of development, where a region is theorized to be dependent on and supportive of an urban core (Perroux 1955). Although developed as a simple theory as to why regions grow, Growth Pole Theory has been used as the base for Growth Center policies in which governments select key industries and centers to receive the investment that in theory will give the urban core a specialization, and the periphery and industry to support. A classic example of a growth center policy is Columbus, OH (Malizia and Feser, 1999). The city is somewhat unique since the public sector was its original growth industry. However, the combination of state government and a research university provided a unique and stable economic base that spurred on regional development with a concentration of and demand for skilled labor. A secondary growth sector was applied through the targeting of manufacturing, which was only viable with after the growth derived from the target sectors had provided a critical mass of public capital and labor (Malizia and Feser 1999).

Growth Center policies can also be applied at a regional scale, with one of the larger examples coming from the Appalachian Region Commission (Wood 2001). Here, designated growth centers receive heavy infrastructural investment which should, in terms of regional production function, augment public capital available in the region to spur growth.

Regardless of the differing understandings and approaches to regional growth that these theories employ, one consistent aspect amongst them is the recognition that regional growth in not ubiquitous. Some regions will grow while others will not. In the neo-classical approach, growth is largely uncontrollable and investment will naturally filter through regions. The endogenous growth theories postulate that certain policy measures can be used to keep a region growing. But, the bottom line is that regardless of the theoretical modeling approach, the movement of investment from region to region suggests that regions will cannibalize each other in the consumption of investment. For one region to receive investment, it must be diverted from another in a process very akin to Schumpeterian (1942) creative destruction. Over time, the movement of capital will lead regions to converge in their relative wealth. This coming together of regional wealth, as measured through per capita income or other outputs measures, is known as Convergence Theory.

The convergence of income or regional output is typically understood as one of four processes: Beta convergence suggests that growth rates in per capita income or output will be faster in less developed areas than more developed ones; Sigma convergence is defined by decreases in the standard deviation of per capita income or output over time; absolute convergence describes a coming together of regional incomes regardless of regional economic structure; and conditional convergence describes a coming together of regional incomes where regional economic structure is assumed to be similar (Barro and Sala-I-Martin 1991). Beta convergence has received the most attention in the literature (Drennan, Lobo and Strumsky 2004) and many papers have supported its existence in some form (Coulombe 2000). In fact, even a simple graph of BEA Economic Region Per Capita GDP in the 1990s expansionary period reflects both beta and sigma convergence (Figure 1). Initially there is a clear distinction between BEA Regions of wealth and poverty, with New England, the Mideast, and the Far West clearly separated from the rest of the nation. Through the decade, growth was comparatively slow for the regions of wealth, especially the Far West, while the regions of initial poverty caught up to the three of initial wealth suggesting beta convergence. While the initially poorer regions have not surpassed those initial three, the gap in distribution has closed indicating a sigma convergence process as well.

Within beta convergence studies specifically, there is a generalized framework for convergence testing (Baumol 1986). This framework is typically applied in an OLS regression, a method that can be ill suited to spatial data (Anselin 1988; Rey and Montouri 1999). Aside from the problems relating to spatial data and regression, this generalized model has been applied to studies ranging from counties to international levels of spatial aggregation (Henley 2005). With this universal application of a potentially mis-specified model, it should come as no surprise that there has been conflicting evidence in the empirical testing for beta convergence.

The goal of this dissertation is to explore the effects that spatial dependence and spatial aggregation can have on beta convergence test results. To do so, the United States

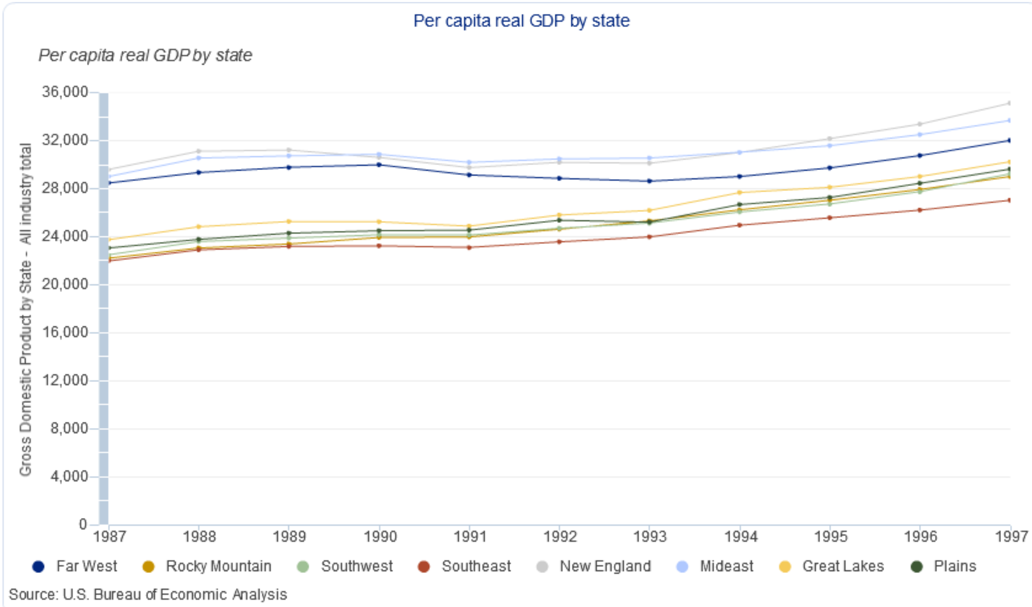

Figure 1: BEA Economic Region Per Capita GDP

serves as the study area for potential convergence from 1970-2004 and beta convergence is tested at three levels of spatial aggregation: states, Economic Areas (EAs), and counties. At each scale, OLS and spatial models are run to test for beta convergence. Results are compared to identify the impact of spatial dependence and spatial aggregation on model results. Pursuant to these goals, this dissertation is divided in to seven additional chapters.

Chapters 2, 3, and 4 consist of a literature review, introduction and discussion of research questions and methods, and descriptive statistics. These chapters work together to establish the research significance and justify the research approach. The literature review in Chapter 2 begins with a discussion of the theoretical basis for convergence theory. The neo-classical growth model is first presented and then extended into a discussion about how this framework for growth will lead to a regional movement of investment and ultimately growth rates. Next, the individual mechanisms that repel and attract investment are discussed to add justification to the theoretical base of the theory and to identify the forces needed to be captured in the regressions. The significance of these theorized forces are examined through a discussion of models used, study areas, and results next are presented and discussed in terms of convergence evidence. The final aspect of the literature review deals with the technical aspects of convergence studies and quantitative geography that can lead to disparate results- spatial dependence and structure, and the Modifiable Areal Unit Problem (M.A.U.P.).

Chapters 3 and 4 build on the literature review to present the research questions, methods for addressing them, and the data used in the models. In Chapter 3, the shortcomings of the current body of literature are presented in order to identify the current holes in convergence research. After identifying those gaps, the goals and research questions of this dissertation are introduced. More specifically, the goals of this dissertation are to examine and explain the spatial structure of convergence, to identify and explain the impact that spatial effects can have on model results, and to identify and explain the impacts of spatial aggregation on model results. The approaches to answering these questions and the remaining structure of this dissertation are then presented. The first component of this analysis is presented Chapter 4 where the data are described. In this chapter, the individual data and their sources used in the models are identified. Then, each variable has descriptive statistics run at each level of aggregation, and is mapped by its standard deviation. This chapter concludes with a correlation analysis at each scale to ensure that no multicollinearity problems will arise in the multivariate models.

Chapters 5-7 each explore spatial structure in convergence in a different manner.

In Chapter 5, an Exploratory Spatial Data Analysis (ESDA) is run on the dependent and main predictor variables to determine if spatial dependence is present in the variables of interest, their structure, and the location of clusters of similar values. In Chapter 6, a bivariate unconditional model is run at three scales using OLS and spatial models to identify the strength of convergence evidence and model performance across scales and specifications. Chapter 7 consists of the same multi-scalar spatial analysis expect that a multivariate conditional model is developed as a first step toward explaining regional income convergence. Below, in Table 1, the various iterations of the models used in these chapters and the goals of each are displayed.

Table 1: Model Iterations

Question	Chapter	Scale	Test	Weight Matrix
Identify Presence and Structure of Spatial Effects in Key Variables	5	States, Economics Areas, Counties	Global Moran's I, LISA	Queen 1, Queen 2
Test for Scalar Effects in Unconditional Convergence	6	States, Economics Areas, Counties	OLS	Queen 1, Queen 2
Identify Impacts of Spatial Effects on Unconditional Model	6	States, Economics Areas, Counties	SAR	Queen 1, Queen 2
Test for Scalar Effects in Conditional Convergnce	7	States, Economics Areas, Counties	OLS	Queen 1, Queen 2
Identify Impacts of Spatial Effects on Conditional Model	7	States, Economics Areas, Counties	SAR	Queen 1, Queen 2

Various conclusions and policy implications are presented in the final chapter. Results of the investigations are summarized and tied back to the convergence literature to reinforce the significance and place of this research. Based on these results, policy implications are drawn, mostly with reference to Regionalism and its relationship to economic development. Here, the theory and underlying arguments for regionalism in governance are presented, and the results of these convergence models are fit in to the new call for regionalism. Directions for future research conclude the dissertation.

CHAPTER 2: LITERATURE REVIEW

Neo-Classical Growth and Convergence

In neo-classical growth models, the production of a region is a function of its capital investment, labor, savings, and an exogenous technologic factor (Malizia and Feser, 1999). The returns to capital investment are assumed to be diminishing and technological change is considered to be exogenous. Eventually, when the returns to capital diminish to the point of a regional steady state, the marginal firm will begin to look outside the region for a new location where returns to investment can again be maximized. This movement of firms and capital to new regions to exploit newer and larger returns to investment is what leads to convergence. Simply put, convergence theory states that as a result of these processes of shifting investment, regional disparities in income or output will decrease over time. There are four commonly understood forms of convergence: (1) beta convergence, where the initially poorer regions will grow faster than initially wealthy regions, allowing the poor region to "catch up" to the wealthier regions; (2) sigma convergence, where there is an overall decrease in the standard deviation of income or output over time; (3) conditional convergence, where regional economic structures are assumed to be the same; and (4) unconditional convergence, where the assumption of regional economic structure similarity is not in place. Beta convergence has received a greater degree of study, and will serve as the type of convergence studied in this dissertation.

Convergence is best understood under a Solow-style (1956) growth framework where wages and returns to investment are hypothesized converge over time. If labor and capital are free to move across regions, as returns to investment begin to stabilize in relatively wealthy regions, investment will flow to less developed regions where new capital can be invested and once again achieve the higher rates of return associated with new products and production processes. This assumption is widely accepted (e .g. Schumpeter 1942; Harvey 1985; Hunt 2002). Historically, this has not always held due to primitive transportation networks and heavy products associated with Fordist production that limited plant locations to sites near important inputs or markets (Stafford 1980; Hayter 1997). However, transportation improvements, more flexible production practices, and the lighter products of the fifth Kondratieff have changed the firm location process from the rigidity of Weberian style approaches to a process where intangibles such as easy access for the executive are now considered (Malecki 1997). An effect of this change in the firms' production function is that profitable locations are now more widespread and firms have a wide range of locations and methods to maximize profits. This can take the form of both the construction of new facilities to exploit new returns to capital investment, but also locating branch plants in low wage regions to maximize returns to labor (Helleiner 1973; Park and Wheeler 1983). If firms are indeed profit maximizing in their decision making, we would expect firms to move from relatively wealthy regions with relatively high wages where returns to investment are already declining, to relatively poor regions where new facility construction will allow for the exploitation of lower wages and the opportunity to maximize new returns to capital (Helleiner 1973; Hayter 1997). If there is a fixed amount of capital, the movement of investment from more developed to less developed regions should produce income convergence as the pace of development quickens in the developing region.

Aside from the natural movement of capital and investment made available by technological and production style change, more deliberate efforts to attract new investment have been theorized to cause regional convergence. Notably, the latter half of the 20th Century saw a growth in import substitution and export processing zone policies (Helleiner 1973). These types of policies encourage capital investment requiring certain institutional and infrastructure requirements which can spur further investment in the region. Foreign Direct Investment (FDI) has been cited as a possible cause of convergence (Gertler 2001). While FDI associated with export processing investment can occur for a variety of reasons, presumably firms pursue such a program only if it offers some economic advantage. Barrios, et al. (2003) and Choi (2004) found the availability of cheap labor or other cost minimization mechanisms lure firms from more expensive production regions which, in turn, helped lesser developed regions converge to the modern developed ones. Dunning (1977) adds to the discussion by noting that firms will move to exploit a variety of locational advantages, such as those noted above. However, the role of FDI in convergence is still debatable, as Gertler (2001) finds that over time, foreign owned firms become less "foreign" and adapt their practices to become a functional part of the region.

Government policy has also been theorized to help regional convergence (Gertler 2001). These policies are based upon the idea that firms will not always locate in an optimal location, but simply a profitable one. A typical method for turning an unprofitable region in to a profitable is through the use of governmental subsidies (Smith

1966). These subsidies alter the existing spatial margins of profit for firms with variable cost structures and can turn previously unprofitable locations for a facility in to profitable ones. Applied to convergence, the movement of a firm to a subsidized location will divert investment from the existing wealthy region, causing a decline, and induce growth in the region that is receiving the subsidized investment. While the idea of subsidy-driven factory-chasing as a source of convergence makes intuitive sense, the empirical evidence generally does not support this idea (Lall and Yilmaz 2000; Santopierto 2002). Annala (2003) argues that these industrial recruitment policies have become essentially ubiquitous in the United States, and are thus now a given for any location considered by a mobile firm.

Testing for Convergence

The standard analysis for measuring convergence is an OLS regression where initial income across a set of regions is regressed against income growth rates (Baumol 1986). A negative beta coefficient provides evidence of convergence, implying regions with high initial incomes experienced slower growth. Barro and Sala-I-Martin (1991) introduced the distinction between beta and sigma convergence and found econometric support for beta convergence among U.S. states over a 60-year period. In the papers that followed, the regression approach became the standard (Drennan and Lobo 1999). Quah (1993) criticized this approach arguing that many investigations simply become regressions to the mean. This criticism aside, these papers generally support beta convergence in the United States (Berry and Kaserman 1993; Rey and Montouri 1999), Canada (Coulombe 2000), South America (Magahales, Hewings and Azzeni 2006), and Europe (Armstrong 1995; Houfer and Wogotter 1995). In each of these papers, the level of geographic aggregation varies, but is always some politically defined division. If spatial effects were considered, they typically entered the model as a regional dummy variable (Durlauf and Johnson 1992; Houfer and Wogotter 1995). These regional dummies tended to be significant, though the strength and nature of the association varied with the level of aggregation (Badinger et al. 2004).

The form of the convergence models is where the distinction between conditional and unconditional convergence becomes apparent. In unconditional convergence, the per capita incomes of regions will converge towards each other over time independent of the initial conditions of the region (Galor 1996). That is, the only important variable to study is per capita income, measured in both change and initial levels. In the regression analysis for unconditional convergence, the simple Baumol-style bivariate regression is enough to capture the effects (Islam 2003). However, in conditional convergence models, the right hand side of the regression includes additional explanatory variables (Galor 1996). The inclusion of these additional variables is to account for the assumption that regions have different steady state equilibria (Islam 2003). The inclusion of the additional variables in conditional convergence models also allows for the inclusion of aspects in New Growth Theory, such as measures of human capital, to be included in the models (Lucas 1988).

While the addition of new predictor variables should increase model fit and control for structural differences in regional economies, conditional models are not without their own specification and consistency problems. In this case, opening up the regression to additional variables raises questions of what variables to include and how they should be specified. Typically, conditional models are variants of a standard neo-classical growth model, and frequently have endogenous variables included, though individual specifications vary dramatically. In contrast to the simplicity of the Baumol bivariate model, Higgens et al. (2006) include 41 variables on the right hand side of a county level regression. These include employment specialization in different sectors, governmental policy variables in both service provision and governmental size, and labor quality. Few models contain as many variables as this, but most models generally contain variables accounting for the larger categories noted above.

Employment specialization is one variable that is typically important in convergence models. In the Higgins et al. (2006) model, the significance of FIRE and Entertainment captured two aspects of the modern economy, 1970-1990. The significance of FIRE is consistent with the work of Mack and Grubesic (2012), who note that FIRE specialization was not only a key mechanism for growth from 1977-2007, but is also a good proxy for competitiveness in the modern economy since it is a sector that uses information technology services more heavily than others (Brown and Goolsbee 2000). But not all models account for specialization through a focus on the drivers of change in the current economy. Choi (2004) notes that percent of service employment in a region is significant in 1982-1997 convergence, which is not surprising given the de-emphasis on manufacturing in the latter 20th Century and emphasis on service in the US economy (Hayter 1997). Mora et al. (2005) divide specialization in to two categories; low tech and high tech for 1985-2005 convergence. Regions with a specialization in low tech industries, such as food and beverage provision or textiles, showed no evidence of converging, while regions with a specialization in higher knowledge sectors such as communications and insurance, showed faster growth. Separating the effect of skilled/unskilled labor specialization is also reinforced by Barro and Sala-I-Martin (1995), Sala-I Martin (1996) and Dall'erba and Le Gallo (2008) through an inclusion of primary sector specialization. This type of specialization is used to control for industrial specialization. That is, it offers a proxy for the level of development in region since primary sector activities tend to have the lowest level of spillover effects. Typically, this variable comes back as negative, indicating the more laggard the industrial structure, the worse the prospects for growth. This is further supported by Johnson and Takeyama (2001), who find that manufacturing specialization has no significant impact on state income growth in the last 50 years of the 20th Century. Even with a great specialization in fourth wave production, it did not set up the state for future growth through the fifth, nor did it doom the region as a starting point in the filtering down process. Tying these results together, the employment specialization component in a convergence model becomes a bit clearer; the model needs to be forward looking and account for the importance of skilled labor. Variables that accounted for high skilled, driving sectors of the next wave consistency return significant, while a sole focus on current wave technology does not set up a region for continued growth. These empirical results fit well with the filtering down process described by Park and Wheeler (1983), where older industries move from places of initial investment to places previously on the periphery. In addition, the geographic implications of Kondratieff Cycles, where places with the endowments of inputs needed for the next wave will experience faster development than those who do not also can help explain those results.

Urbanization benefits have also been tested in convergence models. Simply understood, urbanization benefits are benefits external to the firm that are received by simply locating in an urban area (Jacobs 1969). These benefits include ideas and innovations that can come from a diverse population and labor force, better access to the public services that cities provide, a labor force that is more productive due to the benefits of urban life, and access to a variety of support service firms (Nourse 1968). In beta convergence models, these benefits are quantified in a number of ways. The most obvious measures include those measuring population and urbanization directly. Population is a component in several models (Chen and Fleisher 1996, Cho 1994, Garofalo and Yarmik 2002, Rupasingha et al 2002). A measurement of population is relatively straight forward in interpretation; its size represents both the level of urbanity in the study area, as well as the potential labor force in the area. Areas with large population offer the greatest opportunity for urbanization benefits to arise since it is the large population from which the diversity of ideas will arise, as well as the demand for public services for that large population to produce the services that will be attractive to new firms. This is reflected in positive and significant betas for both initial population and population growth rates across models. Urbanization economies can also be included by analyzing the level of urbanity within a region. Typically this is included as a percentage of the population that lives in an urban area, population density, or a dummy to denote urban areas (Connaughton and Madsen 2004, Higgins et al. 2006, Rupasingha et al. 2002). These return as positive and significant predictors, indicating that economic growth is attracted to places with those benefits. Other measures of urbanization benefits are typically captured through the addition of other variables measuring one of the specific benefits, such as measures of amenity, human capital, or diversity (Rupasingha et al. 2002, Garofalo and Yamarik 2002, Sala-I-Martin 1996, Connaughotn and Madden

2004). Results of these are also consistent with urbanization effects as they show a positive relationship between these variables and economic growth. In other words, firms are attracted to large quantities of skilled labor and amenities which are generally available in urban areas.

Other policy measures that influence the cost of production in the region can be included in regression estimations. Broadly understood, these are variables that identify ways in which a governmental agency has taken action to lower regional production costs to levels that will be attractive to a footloose profit maximizing firm. These governmental actions typically involve low tax rates, infrastructure investment, and labor relation legislation. In terms of tax rates, taxes provide an additional cost that can drive up production costs, and serve to slow growth (Bartik 2005). This idea has been tested by Rupasingha et al. (2002), Wasylenko (1991), and Higgins et al. (2006), where tax rates and governmental size are shown to have a negative relationship with economic growth, firm attraction and, in turn, convergence. These studies, however, are contrary to O'hUallachain and Satterhwaite (1992) who find tax rate lowering incentives to be so ubiquitous that they are given minimal consideration by firms and a historic insignificance of taxes on growth until the 1990s (Malizia and Feser 1999). These conflicting results are not surprising as taxes pay for public services, and public services can be attractive to firms and individuals (Tiebout 1956, Gabe and Bell 2004). To account for this other side of the taxes/services relationship, investment in public sector goods is an alternative measure (Garafalo and Yamarik 2002, Rupasingha et al. 2002, Chen and Fleisher 1996, Shioji 2001). Although it makes intuitive sense and has been applied to theoretical models (Barro 1990, Baro and Sala-I-Martin 1992), the quantitative evidence has also been mixed (Shioji 2001). As a subcategory of public capital, highway investment can be used as a predictor variable in convergence equations taking the form of presence of a highway (Rupasingha et al 2008, Johnson and Takeyama 2001), highway expenditures (Annala 2003), or length of highway per capita (Lau 2010). When only transportation access or investment is considered, the evidence becomes more clear: access to transportation matters as regions with better access to transportation grow faster than those that do not. This is an expected result as an improvement in a region's transportation infrastructure lowers transaction costs for firms within it (Richardson 1973) and those transaction costs will serve to attract the mobile, profit maximizing firm (Smith 1966).

A final aspect common in convergence models involves policies controlling the labor side of a firms production costs. Here, instead of simply offering tax incentives and capital investment to keep production costs low in a region, this method involves taking measures to ensure that what attracted business to a bottom up converging region (low wage costs) stays in place for the life of the firm. A typical measure in the United States is to add a variable to account for Right to Work status of a state. Right to Work legislation involves the implementation of open shop laws where at the state level a prohibition of union shops is established (Stevens 2009). The opening of the shop will affect union membership, reduce collective bargaining power, and in turn reduce wages (Carroll 1983). Intuitively, this is a reasonable expectation. However, it becomes much more complicated when data are added to the analysis. Moore (1980) and Wessells (1981) note that states with low wages are more likely to implement Right to Work legislation as a means for attracting new development, thus showing a strong correlation between income and RTW status, though not establishing causation. When initial conditions are controlled for, the evidence is more mixed. Reed (2003) finds that RTW actually posits a significant positive relationship with incomes, implying that the open shops attracted enough investment to spur growth. Farber (1984) and Rupishanga et al. (2002) find that legislation weakening the collective bargaining power of labor organizations is negatively related to economic growth. Part of this inconsistency in results can be attributed to the treatment of the variable and specification of the growth model. Wessels (1981), for example, notes that results of RTW tests with growth models are very sensitive to specification. Regardless of specification, a few things about RTW legislation are apparent; it has effects that can draw investment due to its impact on wages; regions with RTW laws tend to use them as a policy to attract development; and the development that is attracted can, in fact, cause faster growth rates than would have occurred without the laws. So, as a whole, these laws seem to mirror the convergence process.

The Role of Spatial Structure in Spatial Data Analysis and Convergence

Spatial data present a unique set of difficulties for statistical analysis, notably in regression (Anselin 1988). In standard regression analysis (OLS), a fundamental assumption is that the predictor variables are independent of each other. Failure to account for this can lead to model failure related to skewed confidence intervals around the beta coefficients (Kachigan 1990). Further, for the OLS model to be the best linear unbiased estimator (BLUE), all significant predictors must be included and unrelated predictors should not be included (Kachigan 1990). While these assumptions are fine for non-spatial analysis, the inclusion of the spatial element adds another dimension to be considered. Specifically, convergence is an inherently spatial process. The relationship dictated by spatial proximity means that the location of an observation and the values present at its neighbors can also be considered predictors (Anselin 1988). Thus, a simple OLS model will ignore that relationship and be subject to model bias. Two types of spatial modeling approaches exist to deal with these difficulties; spatial autoregressive models (SAR) and geographically weighted regression (GWR).

SAR models deal with the two types of spatial dependence (Anselin 1998). Spatial dependence can take the form of a spatial lag, where the values of an observations neighbors play a direct role in influencing the value at an observation, or a spatial error, where there is a larger regional process influencing the values within a region (Anselin 1988). The distinction between these types of spatial dependence is subtle, but it can be simply understood that a spatial lag model assumes that the values of a neighbor directly cause the value at an observation, where the spatial error indicates spatial association but not direct causation.

The GWR models are used in response to issues of spatial heterogeneity (Fotheringham et al. 2000). In OLS models, it is assumed that there is equal variance across a variable. However, with spatial data it is possible that there may be regional fluctuations in variance. That is, the variance across observations in one neighborhood is not the same as the variance across observations in another neighborhood. OLS is not designed to handle that problem; it operates as if the variance is uniform across space. Failure to account for this will lead to regionally autocorrelated residuals, thus further compounding the problem. GWR models handle this by essentially running separate regression models for each region. Thus, the beta coefficients for a predictor will not be uniform across space.

The early convergence papers including SAR models used relatively large units of US states and European Union regions as units of observation, but they still found the spatial component to be important in the convergence model (Rey and Montouri 1999; Armstrong 1995). More specifically, Rey and Montouri (1999) found not only strong evidence supporting beta convergence in U.S. states from 1929-1994, but also demonstrated that a spatial error model was superior to OLS in predicting Per Capita Personal Income change. In a paper aggregated at sub-regional level in Great Britain, Henley (2005) found that detection of beta convergence was model-dependent and sensitive to dependent variable specification in a 1977-1995 model. His results on model specification were similar to that of Rey and Montouri in that he found the spatial error model to be superior to the lag model. These papers are consistent with Barro and Sala-I-Martin (1995) who found that the growth rate of a county bears a relationship with the initial income level of its neighbors in the United States 1880-1990. Fingleton (1999) also found evidence for convergence in European Union regions although the strength of spatial association was again dependent on model specification. In a paper not directly testing convergence, but offering support for it anyway, Le Gallo and Etur (2003) found both significant autocorrelation in per capita income growth and an inverse relationship between initial per capita GDP and its growth rates in European NUTS 2 regions.

The Modifiable Areal Unit Problem in Spatial Data Analysis

Aside from the model specification problems that spatial data can cause in non-spatial models, the issue of areal unit selection also poses a problem for model validity. Though the issues of regional definition and study area size are known to be central to any type of geographic study, the actual methods for choosing a study area and level of aggregation should be tailored to the particular type of study (Isard 1956). This area for concern seems to be largely ignored in the convergence literature, as the variety of aggregation units (states, Economic Areas, NUTS regions, MSAs) has led to disparate results. While the ideal region for convergence testing has yet to be fully explored, the effects of different areal unit selection on regression analysis are well known. In this section they will be presented in preparation for a specific quantitative analysis to follow.

The problem of differing areal unit selection causing differing results on the same study is known as the Modifiable Areal Unit Problem (M.A.U.P.) and was first introduced by Gehlke and Biehl in 1934. In this pioneering study, the authors found that correlation coefficients varied with aggregation unit size, where smaller units produced a smaller coefficients of determination. Computationally this should be expected, as larger units of aggregation will mask small scale variations and will pull the areal average towards the overall mean. Since then, the work on this topic has expanded enough where M.A.U.P. effects can be understood in two key areas; scale effects, and zoning effects. At the core of this problem is the fact that in spatially continuous data there are numerous ways to aggregate (Openshaw and Taylor 1979). It is this variability that makes spatial data unique and thus different from the data used in traditional inferential statistics (Cliff and Ord 1981).

Scale effects are the type of problems that are similar to those experienced by Gehlke and Biehl, where results change as the level of aggregation increases or decreases within a constant study area; i.e. the change in results that census tracts would produce instead of census blocks in the same state (Openshaw and Taylor 1979; Wong and Lee

2005). Outside of the original study of Gehlke and Biehl, this phenomena has been demonstrated in key articles by Fotheringham and Wong (1999) who demonstrated that a simple switch from census blocks to census tracts as the units of aggregation in a linear regression of mean family income against the standard socioeconomic predictors could strongly influence not only the R^2, but also the individual p-values of the predictor variables. In essence, the predictors for mean family income could be entirely different based simply on how the data was aggregated. This is a similar result to the keystone paper on M.A.U.P., "A Million or so Correlation Coefficients" by Openshaw and Taylor (1979). Here, the authors used the percentage of representation in the state legislature and percentage of the county over 60 years of age and ran correlations from the county level to six large zones defined by urban/rural definition. The results were quite striking as the correlation coefficients ranged from -.2651 to .8624. Not only does this represent a large range of association based on simple aggregation, the fact that the correlation coefficients actually range from positive to negative values presents a real problem for interpretation. While the data came from the same source and were processed in exactly the same manner outside of aggregation level, this paper shows that it is possible to find exactly the opposite results for the same question, data, and study area.

M.A.U.P. problems present a similar problem in the zoning problem. This issue, again, relates to how results may vary depending on how individual data are aggregated within a consistent study area. This differs from the scale problem in that the zoning problem occurs when the results change from regrouping aggregation units at the same scale (Fotheringham et al. 2000). Openshaw and Taylor (1979) also explored this issue using the same Iowa dataset used in the scale problem analysis to show the rearranging the data to 12 units in different manners would produce correlation coefficients between -.97 and .99. This result reflects the importance that spatial aggregation choice can have on results, as the results range from near perfect correlation in both directions. In essence, this experiment found statistically significant evidence that the same variables at the same scale of analysis were positively related and negatively related, as well as finding situations in which the null failed to be rejected. With this variability, the authors note that it falls to the researcher to be careful in his research design and not only ask what (s)he wants to investigate, but also what scale and aggregation would be appropriate to answer the question give the data available. Paez and Scott (2004) add to the researchers task by noting that any result must be interpreted as only one of several possible outcomes. Thus, before any theory can be developed, it is important that a result be demonstrated to be replicable consistently.

While a natural reaction to the M.A.U.P. would be that aggregate spatial data is worthless, that conclusion is not a pragmatic one since many data are not available at the individual level (Fotheringham et al. 2000). Other solutions include the use of GIS techniques to find “optimal zoning” arrangements (Horner and Murray 2002). However, this too can be a problematic solution as any optimization routine is still subject to human specification errors. A more general rule of thumb that can be used to help minimize M.A.U.P. problems is to use the smallest aggregation units possible (Wong 1996; Fotheringham 2000 et al). And even then, it is entirely possible the smallest unit possible for the analysis is not the smallest unit available, since spatial processes define themselves (Isard 1956).

Exploratory Spatial Data Analysis

In the non-spatial context, Exploratory Data Analysis (EDA) is a technique that has a rich history (Behrens 1997). As opposed to confirmatory model building that seeks to explain and add validation to existing theories, EDA utilizes a broad range of statistical descriptive techniques (Brehens 1997). It involves the application of statistical and graphical tests on a dataset with as few assumptions about the underlying structure as possible (Tukey 1977). Without assumptions of underlying structure, EDA typically involves the use of standard data descriptives being run on all data and their possible combinations (Anselin 1988). Tukey (1980) argues that EDA is a fundamental part of a complete research agenda; before attempting confirmatory analysis, the underlying relationships in the data need to be fully explored and understood which then serve as the point of departure for the construction of theories and hypothesis testing.

Exploratory Spatial Data Analysis (ESDA) is a method of EDA where the spatial components and relationships in the data are specifically examined. Space, or more specifically the role of location as an underlying factor influencing attribute values, is an important consideration when engaging in any confirmatory analysis. Failure to account for spatial dependence can lead to specification errors (Anselin 1988). Spatial data relationships can take the form of either spatial dependence or spatial heterogeneity (Anselin and Getis 1992). Methods for examining spatial relationships involve specialized geostatistical tests that make use of traditional EDA output, such as a scatter plots and geographic representation through maps (Unwin and Unwin 1998; Anselin 2005). The specific exploratory tests on spatial data include both global and local tests for spatial association. ESDA can employ a variety of statistics such as Moran's I, Getis-

Ord G*, Geary's C, and Anselin's Local Indicators of Spatial Association (LISA). Exploratory in nature, these tests are not used to confirm any existing hypothesis; they simply test the distribution of a variable across space. In other words, they test to see if the spatial distribution of a variable is indeed random which, in a sense, is no different than testing for normality (they are merely examining the spread of the data).

At the global level, there is an assumed degree of spatial autocorrelation due to things such as physical geography and the built environment (Ord and Getis 2001). As such, in many cases it may seem that spatial dependence in observations is a reasonable expectation (Anselin 1995). However, simple proximity does not by itself indicate spatial dependence. Only when global measures of spatial autocorrelation are significant can spatial effects associated with relative location be confirmed. So, a good starting point for any ESDA involves examination of the global spatial autocorrelation statistics.

Measures of global spatial autocorrelation detect the presence of spatial dependence. The most frequently used statistic is Moran's I (Cliff and Ord 1981). With reference to PCPI using BEA Economic Areas (EA) as our locations, Moran's I is expressed as:

$$I = n\Sigma\Sigma w_{ij}(x_i - \bar{X})(x_j - \bar{X}))/\Sigma\Sigma w_{ij}\Sigma(x_i - \bar{X})^2 \qquad (1)$$

Where:

x_i = PCPI in Economic Area *i*

x_j = PCPI in Economic Area *j*

W= spatial weight matrix

n= number of observations

From Equation 1is it clear that Moran's I is a function of only two components --

the attribute value being studied and a spatial weight matrix. The numerator is the covariance of PCPI at location *i* with the values of the other locations *j* multiplied by the spatial weight matrix. If the locations being compared are not defined as neighbors, the weight matrix value reduces to 0, effectively removing them from the calculation. Clearly, the spatial weight matrix is of special importance. Typically, a simple binary or stochastic matrix is used (Wong and Lee 2005), although the number of neighbors and type of contiguity (Queen or Rook) needs to be determined through a combination of theoretical understanding and descriptive statistics (Anselin 2005). Alternative methods for determining neighbors include the k-neighbors approach or distance bands. K-neighbors-defined matrices assign neighbor values to the k neighbors nearest to an areal unit, where k is a static number defined by the analyst. Distance bands, on the other hand, simply define neighbors as those areal units within a specified distance of the study area. Since the k-neighbors and distance band approaches are reliant on distance, in large study areas they are subject to distance distortion associated with certain map projections as well as errors associated with a lack of uniformity in areal unit size. Contiguity measures, however, are not subject to those sources of error.

The values for Moran's I range from -1 to 1, where -1 indicates perfect negative spatial autocorrelation (low values and high values cluster around each other) while a value of 1 indicates the clustering of similar values. The expected value for Moran's I is not 0; rather it is based on the number of observations, and is always negative (Wong and Lee 2005). The expected value for Moran's I is given by Equation 2:

$$E_I = -1/(n-1) \tag{2}$$

Where:

E_I is the expected value in region I

If Moran's I indicates spatial autocorrelation at the global level, then examination of spatial autocorrelation at "lower" levels is warranted.

Local spatial autocorrelation statistics are those that identify individual "hot spots" and "cold spots" within the study region. Hot spots are the spatial clusters of similarly high values, while cold spots are the spatial clusters of similarly low values. A true local statistic based on one of the global metrics gives an indication of spatial clustering of values around a similar value, adding up to the global statistic (Anselin 1995). In essence, local statistics decompose the global statistic into its component values by area and test for statistical significance in the cluster. Typically, local autocorrelation is measured through Anselin's Local Indicators of Spatial Association (LISA), a local version of the Moran's I (Anselin 1995). LISA statistics are calculated for each areal unit and hot and cold spots can be found through mapping the LISA statistics. Continuing with our PCPI example, LISA is defined in Equation 3 as:

$$I_i = z_i \Sigma_j w_{ij} z_j \tag{3}$$

I_i = Local Moran's I at EA i

z_i = Deviation from the mean PCPI at EA i

w_{ij} = Spatial weight matrix value for EA i and j

z_j = Deviation from the mean PCPI at EA j

As is the case with the global Moran's I, LISA statistics are based upon attribute values at a given location and those of its neighbors as defined by the spatial weight matrix. Interpretation of LISA statistics is the same as the global version: positive values indicate clusters of similar values, while negative values represent clusters of dissimilar values. Aside from simply using the LISA statistic to identify clusters of (dis)similar activity, it can also be used to identify outliers that may present undue leverage in the calculation of the global statistic (Anselin 1995).

In ESDA, one assumption is consistent across the global and local investigations: spatial relationships matter and influence the presence, absence, and magnitude of phenomena among neighbors. This assumption is well suited to the examination of beta convergence which, by definition, assumes spatial relationships among regions. The ability of ESDA to detect beta convergence comes from both the global and local metrics. ESDA metrics can be applied to detect beta convergence through an analysis of changing regional income or output over time. If beta convergence is present, those regions starting off with lower incomes or output should show faster growth than those regions starting off with higher incomes or output. Since income is known to have a high degree of spatial autocorrelation, metrics showing change are expected to cluster with the large values (high growth rates) clustering in the initial cold spots; similarly low values (low growth rates) should cluster around the initial hot spots. Globally, this will be reflected in a large positive Moran's I statistic. In the presence of spatial autocorrelation, LISA clusters should show hot spots in the initially higher income regions and cold spots in the initially lower income regions. The relative changes (beta convergence) should be the spatial inverse of the initial conditions with areas of low initial values showing up as hot spots of faster growth, and initial hot spots showing as cold spots of slower growth.

Summary

In this chapter, a review of the beta convergence literature, spatial effects in convergence and Exploratory Spatial Data Analysis (ESDA) was presented. Beta convergence is a subset of convergence theory that hypothesizes that regions of initial poverty will grow faster than regions of initial wealth (Baumol 1986). This faster rate of growth comes from the movement of investment from regions of wealth to regions of poverty as firms seek to maximize returns to investment (Barro and Sala-I-Martin 1991). To test for beta convergence, the typical model is a bivariate regression where income change is regressed against initial income levels, with a negative beta coefficient indicating the presence of beta convergence (Baumol 1986). This approach has been applied from the international to county levels, and has produced inconsistent results regarding the strength and presence of this process (Drennan and Lobo 1999).

Two potential reasons for this inconsistency come from spatial dependence and the Modifiable Areal Unit Problem (M.A.U.P.). Spatial dependence is a unique problem in spatial data, where observations are not independent across space, which violates the assumption independence amongst observations in regression (Anselin 1988). The M.A.U.P. in this case refers to the aggregation problem, where model results vary simply because of how the data is zoned across space (Gehlke and Biehl 1934). The application of these theories to convergence analysis is simple. The standard OLS ignores the spatial dependence known to be in income (Rey and Montouri 1999), and the variety of scales is the definition of disagreement based upon zoning. The goal of this dissertation is to investigate the role that these problems may play in beta convergence. In the following chapter, the specific research questions, research methods, and data sources will be presented.

CHAPTER 3: RESEARCH QUESTIONS AND METHODS

Research Questions Still Open

As noted in the literature review, there is quite a bit of research still to do on the topic of convergence. First and foremost, work still needs to be done to verify if convergence is actually occurring. However, the real potential for research lies in how convergence is actually tested. The traditional OLS approach introduced by Baumol needs to be modified to include spatial aspects. The fact that the typical dependent variable (regional income/output) is known to be strongly spatially autocorrelated provides the first clue to this necessity. The scant existing work applying spatial models to convergence adds further support to the need for a spatial modeling approach, as they all point to the significance of the spatial component in the model. This statistical validity, of course, is just secondary to the fact that convergence is a regional process by definition, and thus well suited to spatially explicit models.

In addition to the need for spatial modeling approaches, perhaps the biggest shortcoming of the existing literature is inattention paid to the underling spatial structure of convergence and its related variables. Additional work here needs to come in two areas. First, relating to the spatial models themselves, while there is some support for the spatial error model there are simply too few investigations to say this structure is consistent across types of measurement and regions. Second, getting to a larger problem in the existing literature, the "optimal scale" for the analysis that will produce the best model fit and diagnostic performance has yet to be investigated, let alone found. The current variation of scale includes both international and national scales, but also aggregation units ranging from smaller units such as counties to relatively large units such as states. The problem related to this should be rather obvious. Neither counties nor states are functional entities. Counties are small enough that they can be aggregated up to create functional economic areas, whereas states include several independent economic areas. Thus, smaller levels of aggregation artificially inflate the spatial component results, while states could artificially deflate the spatial dependence, and thus results.

In order to properly investigate these concerns, future research needs to include several types of analyses. To assess spatial structure and dependence, a variety of techniques are available. To identify the neighborhood of spatial influence, ESDA methods allow us to detect the extent of spatial association, the strength of association, as well as the appropriate neighborhood matrix to use. Spatial autocorrelation statistics (global and local) offer the ability to identify the strength of the spatial association, as well as to identify the regions of hot and cold spots subject to the convergence process. After the appropriate neighborhood is identified, the appropriate SAR model can be identified through a Lagrange Multiplier (LM) test. For the M.A.U.P. analysis, the approach of Openshaw and Taylor can be replicated. Here, the convergence models should be run at a variety of scales in the same study area in order to compare results. By doing so, this type of analysis will eliminate the "only one possible answer" problem associated with single scale analysis. Thus, the overarching trends of the data can be extracted to determine if the influence of the predictor variables is consistent across scales. This consistency will then enable a greater degree of rigor to the question of convergence, as well as the causes of the convergence itself.

Research Questions

As noted in the previous section, there are still several questions open regarding the role of space and spatial structure in convergence testing. Aside from the relative uncertainty of the extent of spatial influence in convergence models, there is still the lingering question of appropriate scale for convergence testing. The variation of spatial structure can provide issues relating to model validity, as failure to define an appropriate neighborhood for the spatial regression will not capture the full effects of the spatial processes, and will thus cause model mis-specification. The issues of aggregation can be a bit more tricky and dependent on scale of analysis. International and domestic convergence processes could be parts of rather different economic forces. For example, FDI may play a much larger role in international convergence than in domestic convergence. Further, the role of FDI may depend on the individual economy of the nation; for example, a poor nation with export processing zones can have a larger potential for FDI than one that does not. International convergence studies also have to deal with a lack of uniform sub-national definitions and data reporting issues. The data reporting and sub-national regional definitions are largely consistent within domestic studies, and thus should serve as a reasonable starting place to address M.A.U.P. issues described in the previous section. This dissertation seeks to answer the questions related to spatial structure and unit aggregation using the United States as a study area.

The first component of this dissertation focuses on the spatial structure of convergence. In this section, ESDA techniques are applied to the typical beta-convergence dependent variables (PCPI change) and predictor variables (initial income levels), at three level of aggregation; counties, Economic Areas (EAs), and states. A global statistic, Moran's I, will test for the presence of spatial dependence to identify if there is indeed a spatial structure in the convergence process and the strength of that presence in small to large units of aggregation. A local statistic, Anselin's Local Indicators of Spatial Association (LISA), will be able to identify the individual clusters of change, and test for the significance of those relationships. Both of these statistics are applied at two neighborhoods; first order queens and second order queens. Applying these tests to multiple neighborhoods is a standard approach in ESDA which allows for the comparison of significance between neighborhoods in order to determine the "true" neighborhood of influence. Although there are several ways of defining a neighborhood (inverse distance, k-neighbors, queen contiguity, rook contiguity), Rey and Montouri (1999) found that a simple contiguity neighborhood definition produces the best results in convergence models of the United States. Also, given the goal of this dissertation is to apply the same model at different scales, anything other than this simple matrix would be modeling a much different process at different scale, i.e. the neighbors captured though a k-neighbors approach will capture different regional process at the state level than the county level, while contiguity will only capture the influence that a neighbor has on the observation.

The second component of this dissertation involves applying the lessons of the investigation of spatial structure to create a better confirmatory model. Although the typical test for beta convergence is an OLS regression, research described in the previous section suggests that this is not an appropriate test given the strong presence of spatial dependence. With insights on the underlying spatial structure, the spatial regression used here will provide a concrete test that will account for spatial structure in a manner that produces robust results. As in the ESDA section, states, EAs, and counties are used as units of aggregation and then results are compared across scales

These analyses offer several contributions to the literature. First, they address the M.A.U.P. issues in convergence by testing for convergence at a variety of scales while using the same data. In the existing literature, there is no consistent level of aggregation, and the papers are generally at one scale. Thus, comparisons across papers are also subject to comparing results from different datasets and experiments. Here, that problem is eliminated. A second contribution also deals with identifying the underlying spatial structure in convergence. Since convergence testing is relatively unexplored in spatial models, a comprehensive study has yet to identify the true spatial structure. By using the ESDA and statistical tests, this component of the dissertation addresses the question of "Just how strong is the spatial dependence in PCPI change, and is what the extent of that influence?" as well as identifying if spatial dependence varies by scale. In addition, the application of the spatial models in comparison to the traditional OLS model at a variety of scales will allow for a full comparison between the traditional test against the spatial one, to explore the improvement in model validity and explanatory power with the inclusion of a spatial component. Finally, the addition of the conditional model built out of the traditional bivariate model allows for the comparison of model results to help understand the nature (conditional or unconditional) of convergence in the United States. Also, in the conditional model, components outside of simple initial income levels will be tested for their influence on the convergence process. If significant in this convergence model, these additional factors will lend credence to more endogenous factors that spill over in to the policy realm.

Study Area and Methods

Convergence is an inherently spatial and temporal process, so any study needs to find a method for accounting for space and time. The time period covered is 1970-2004, with the contiguous United States as the study area. This span offers several advantages. First, 1970 is start of the last decade clearly in the fourth Kondratieff wave (Hayter 1997). The fourth wave was characterized by Fordist mass production that gave rise to the industrial dominance of the Northeast. As the economy transitioned into the fifth Kondratieff, there was a shift in production to more flexible process and knowledge-based products (Hayter 1997). This transition in production processes and important sectors helped drive the regional growth of the South and decline of the Rust Belt, a regional change associated with the convergence process (Bishop 1992). The end period, 2004, was chosen as it is the last time period before the effects of Hurricane Katrina, an event so economically catastrophic that the economy of New Orleans has yet to recover. Thus, 2004 will offer the most recent data year without Katrina which provides a textbook example of an exogenous event effecting data. Further, there already is evidence of a convergence process occurring in the United States during this time period (James 2010).

In the first section, Per Capita Personal Income (PCPI) change will be tested using Moran's I and Anselins' LISA at county, Economic Area, and state scales using a first order and second order queens neighborhood weight matrix. The use of multiple scales covering the same regional and variables is consistent with the M.A.U.P. analysis used by

Openshaw and Taylor (1979). By comparing the results across scales, this dissertation will be able to provide quantitative evidence showing how convergence evidence can vary by scale. The individual statistical analyses each examine the underlying spatial structure of PCPI change in an individual method. The multiple spatial weight matrix analysis is a standard ESDA approach. Doing so allows for the proper definition of the spatial weight matrix, a necessary step in all of the following statistical analyses.

Once the appropriate neighborhood definition has been created, it can then be used in the calculation of the global and local spatial statistics. For the global level, the standard method of analysis is the Moran's I (Cliff and Ord 1982). This tests for spatial autocorrelation past the expected association represented in Tobler's Law (Tobler 1970; Anselin 1995). The global test does not identify any individual clusters, but it does provide a mechanism for testing the strength and type of association. Values for Moran's I range from -1 to 1, with negative values indicating an unnatural clustering of dissimilar values, while positive values indicate a clustering of similar values. The expected value is not 0 but a slightly negative number based upon the number of observations, so interpretations must be checked against the p-value of the statistic. (Wong and Lee 2005). For this dissertation, the global Moran's I is calculated in Equation 4:

$$I = n\Sigma\Sigma w_{ij}(x_i - \bar{X})(x_j - \bar{X}))/\Sigma\Sigma w_{ij}\Sigma(x_i - \bar{X})^2 \tag{4}$$

Where:

x_i = PCPI in Economic Area *i*

x_j = PCPI in Economic Area *j*

W= spatial weight matrix

n= number of observation

As Moran's I values get closer to -1, the value at one location is in stark opposite contrast to the same value of its neighbors, while values approaching 1 indicate an unnatural similarity of values between and observation and its neighbors. The importance of the neighborhood definition is shown by the presence of *W* in both the numerator and denominator. Since the equation involves a summation comparing the values at *i* to the values at *j*, *W* provides the mechanism to differentiate between neighbors and non-neighbors. Thus, an appropriate neighborhood definition is important to calculate if the statistic is going to be valid. By applying both global and local statistics at different neighborhood definitions, it is possible to find the neighborhood that has the strongest (most significant) effect, which in turn is the neighborhood of influence to consider when modeling.

The local statistic, Anselins' LISA, is a local version of the global Moran's I (Anselin 1995). As a local statistic, it decomposes the global value into its component parts, allowing the individual clusters of significant spatial association to be identified. Similar to its global counterpart, the interpretation of the LISA statistic is that positive values indicate positive spatial autocorrelation, and negative values indicate negative spatial autocorrelation. These clusters are identified as either “hot spots”- clusters where the values of an observation and its neighbors are unnaturally similar and high- and “cold spots”- clusters where the value at an observations and its neighbors are unnaturally low. In addition to the identification of spatially clustered dependent activity, the LISA statistic also allows for a p-value to be assigned to the cluster so that their relative strength can be assessed. The LISA statistic is calculated (Equation 5) as:

$$I_i = z_i \Sigma_j w_{ij} z_j \tag{5}$$

Where:

I_i = Local Moran's I at area i

z_i = Deviation from the mean PCPI at area i

w_{ij} = Spatial weight matrix value for areas i and j

z_j = Deviation from the mean PCPI at area j

Similar to the Global Moran's, the spatial weight matrix is of utmost importance in the proper application of this statistic, as it defines who the neighbors are in the comparison. An improper neighborhood definition opens the door to flawed comparison, and an improper understanding of the spatial structure of convergence. By finding the appropriate level for neighborhood definition, this section will provide a more thorough analysis of the spread of spatial dependence in convergence studies. Doing so then allows for a more robust and representative spatial weight matrix to be included in the confirmatory models.

The application of the spatial statistics on the key convergence variables at variety of scales also allows for a discussion of the M.A.U.P. scale issue in a manner similar to Openshaw and Taylor (1979), an approach which is standard for M.A.U.P. analysis. In the standard M.A.U.P. analysis, correlation tests are run among two variables at an increasing scale, and the change in both the correlation coefficient and its significance are compared. Moran's I operates in a manner similar to simple correlation (though computationally different); two variables are compared for each observation. In this case it is PCPI change and 1970 PCPI as observations, and neighborhood PCPI. The comparison across scales facilitates a discussion as to what scale will influence the structure of spatial dependence in convergence and will set the stage for a further confirmatory model that is specified correctly based upon the scale of analysis.

Lessons learned regarding spatial dependence in PCPI are applied to the traditional Baumol-style convergence model in Chapter 6. At each scale, the traditional Baumol-style OLS regression is run and then compared to a spatial autoregressive model. For the spatial models, a spatial weight matrix, *W*, is included. First order and second order queens neighborhoods are used and results are compared as in the ESDA section. The type of spatial model, error or lag, is determined through a Lagrange Multiplier test performed on OLS. Equation 6 represents the Baumol-style OLS model, Equation 7 the spatial lag model, and Equation 8 the spatial error model.

$$C_i = k + \beta * PCPI_i^{1970} + \varepsilon \tag{6}$$

$$C_i = k + \beta * PCPI_i^{1970} + \beta W\lambda + \varepsilon \tag{7}$$

$$C_i = k + \beta * PCPI_i^{1970} + \beta W\varepsilon + \mu \tag{8}$$

Where:

C_i is PCPI change in area *i 1970-2004*

$PCPI_i^{1970}$ is PCPI in area *i* in 1970

W is the spatial weight matrix

λ is the spatial lag of C_i defined by weight matrix *W*

ε is the vector of spatially autocorrellated error terms defined by weight matrix *W*

μ is the vector of errors

In these models, the presence of beta convergence is indicated by a negative coefficient on 1970 PCPI. This negative coefficient indicates that the higher the level of

1970 PCPI, the more detrimental effect it has on PCPI change levels. A relatively large level of PCPI in 1970 is theorized to drive slower growth from 1970-2004. The effect of space in the spatial model is shown through the p-values of the associated terms. A significant p-value indicates that the value of PCPI change at an observation's neighbors is a significant predictor for PCPI in the observation itself. For evaluation across models, the diagnostics for OLS such as model fit (Log-Likelihood) and residual normality checks are used for the Baumol-style model comparison across scales. In addition to the traditional OLS diagnostics, residuals are also tested for spatial autocorrelation using Lagrange Multiplier and Local Moran's I tests. If there is spatial dependence in the residuals, they are not independent, indicating the need for a spatial model. For the spatial models, the appropriate test for model fit are the Log-Likelihood test (Anselin 2005). Residuals in the spatial error model are also tested for normality and heteroskedasticity through the same mechanisms as the OLS tests. These tests are run and then compared across scale and models.

Chapter 7 takes the lessons learned about spatial dependence in the dependent variable in convergence testing and applies them to a confirmatory conditional model at the same three scales. PCPI change will again serve as the dependent variable; the major explanatory variable in a standard convergence test will be 1970 PCPI. If the convergence hypothesis holds, the beta for 1970 PCPI should be a negative number indicating healthier the regions in 1970 experienced slower growth in PCPI over the study period. The spatial dependence component will be included in the model through a SAR variable, but the specification as spatially lagged or spatial error component will be determined after comparing the model diagnostics for both. Other predictor variables will include measures for other hypothesized reasons for convergence: Right to Work status, population, urban/rural mix, and connectivity to larger markets. However, aside from these hypothesized drivers of convergence, perhaps the most important variables in the model relate to industrial specialization. One of the key characteristics of the change from the fourth to fifth Kondratieff is that the production paradigm associated with western economies involved a shift in demand from unskilled to skilled labor. In the manufacturing sector, the products best produced through Fordist mass production are no longer profitable to produce in the United States and flexible manufacturing plants, as well as plants associated with new early life-cycle stage products, have become increasingly important in this sector. Also important to the growth of the fifth Kondratieff is the growth of skill based tertiary employment. In terms of specific sector specialization to include, these variables will be included at the two-digit SIC level for the FIRE and Service sectors. FIRE employment, according to Mack and Grubesic (2010) can serve as a proxy to capture both knowledge-based and other skill driven sector specializations in data sets without that definition specifically. For the 1970 SIC codes used here, that is the case. Service employment specialization is also included due to its dominant role in fifth Kondratieff U.S. employment. Specialization is calculated by a Location Quotient. The models take the following forms with Equation 9 representing the OLS, Equation 10 the spatial lag, and Equation 11 the spatial error:

$$C_i = k = \beta * PCPI_i^{1970} + \beta * RTW_i^{1970} + \beta * P_i^{1970} + \beta * R_i^{1970} + \beta * C_i^{1974} + \beta * LQS_i^{1970} + \beta * LQFIRE_i^{1970} + \epsilon \tag{9}$$

$$C_i = k = \beta * PCPI_i^{1970} + \beta * RTW_i^{1970} + \beta * P_i^{1970} + \beta * R_i^{1970} + \beta * C_i^{1974} + \beta * LQS_i^{1970} + \beta * LQFIRE_i^{1970} + \beta W\lambda + \epsilon \tag{10}$$

$$C_i = k = \beta * PCPI_i^{1970} + \beta * RTW_i^{1970} + \beta * P_i^{1970} + \beta * R_i^{1970} + \beta * C_i^{1974} + \beta * LQS_i^{1970} + \beta * LQFIRE_i^{1970} + \beta W\epsilon + \mu \quad (11)$$

Where:

$PCPI_i^{1970}$ is 1970 PCPI in location *i*

RTW_i^{1970} is 1970 Right to Work status in location *i*

P_i^{1970} is 1970 population in location *i*

R_i^{1974} is 1974 USRA rurality score

C_i^{1970} is 1970 connectivity in location *i*

LQS_i^{1970} is the 1970 Location Quotient for Services in area *i*

$LQFIRE_i^{1970}$ is the 1970 Location Quotient for FIRE in area *i*

W is the spatial weight matrix

λ is the spatial lag term

ϵ is the spatially autocorrelated error term

PCPI comes from the Bureau of Economic Analysis Regional Economic Information System (REIS) and is expected to have the same negative sign if convergence is present. Right-to-Work status is classified as a binary variable, where states with Right to Work legislation in 1970 are classified as “1” and others are “0”. This information comes from the National Right to Work Legal Defense Foundation (www.nrtw.org). It is included to account for governmental policy influencing the production costs within a region and, although the evidence has been mixed, the expected sign for this variable is positive, indicating that a control on wages will make the region more attractive for growth. Connectivity is defined as the distance from a weighted centroid to the nearest completed interstate highway in 1970. Highway information is from the Federal Highway Administration (www.fwha.dot.gov), and population is from the National Historic GIS (www.nhgis.org), and that variable was calculated in GIS. Connectivity is included to account for governmental investment to provide infrastructure to the region as a reduction in cost structure, as well as how integrated the region is to the growing economy of the time period. The expected sign is negative, indicating that the further away a region was from highway access, the slower it grew. Two variables are included to account for urbanization effects: 1970 population and 1974 urban-rural continuum classification. Population is provided by the National Historic GIS, and should account for the size and diversity of the labor force, as well as a proxy for urban services available. The expected sign for this variable is positive, reflecting their theorized positive effects on growth. The urban-rural classification is included for the earliest year available, 1974, and is provided by the USDA (www.ers.usda.gov). These codes range in value from 1-9, with scores of 1-3 indicating metro counties, 4-7 indicating non-metro counties with urban populations, and 8-9 being completely rural counties. This is included as a measure for the level of urbanity, as well as concentration, within a region. With the required reversal for population weighting, the expected sign is positive as well. The final two variables included are industry specific, to measure the level of industrial specialization in a region; 1970 FIRE location quotient, and 1970 Service location quotient. Both variables are included to capture early specialization in sectors that were drivers in the latter 30 years of the 20th Century economy, and thus have expected signs of positive. Employment data also came from the National Historic GIS. Table 2 displays all of the variable information in table form.

Table 2: Variables

Variable	Variable Name	Source	Expected Sign
1970 PCPI	PCPI	BEA REIS	Negative
1970 Right to Work Status	RTW	National Right to Work Legal Defense Foundation	Positive
1970 Population	P	National Historic GIS	Positive
1974 Urban-Rural Continuum Code	R	United States Department of Agriculture	Positive
1970 Connectivity	C	Federal Highway Administration	Negative
1970 Service Location Quotient	LQS	BEA REIS	Positive
1970 FIRE Location Qoutient	LQFIRE	BEA REIS	Positive

The conclusion will include a section on the policy implications of the results and directions for future study. Policy implications are the central component of the real world practical applications of this study. Economic development policy takes place at a variety of governmental levels; state level, such as eminent domain for economic development reform or right to work legislation (James 2008); or localized industrial recruitment and industrial targeting (Bartik 2005; Fisher and Fisher 2004).

The implication of this regional process is that true growth occurs at a regional level, as explored by Higgins and Savoie (1995). This Regionalism approach fits quite well with the understandings of conditional convergence, since in the conditional models, the regional effect is not simply limited to returns to investment, but also present in the factors of endogenous growth, such as a regional well-educated work force or a well-developed transportation network. This chapter concludes with a discussion of Regionalism, its approach to governance, how the results of this analysis fit in to the Regionalism literature, and are used to establish a future line of research questions related to economic development policy.

CHAPTER 4: DATA PROCESSING AND DESCRIPTIVE STATISTICS

Data Processing

As a spatial analysis, the data for all models need to be stored in a manner that can be utilized by a Geographic Information System. In this case, the program needed for the regressions is GeoDa, which necessitates that data be stored in an ESRI shapefile format. The first step is to construct a base shapefile for each scale to which attribute data can be joined. The base layers for counties and states are provided by ESRI and projected to a Lambert Conformal Conic projection. Economic Areas are constructed from the county shapefile, by joining the BEA spreadsheet of Economic Areas to the county shapefile and dissolving by EA name. In the county shapefile, independent cities in Virginia are dissolved in to their surrounding county for the purposes of defining a spatial weight matrix, as the independent cities would be completely nested around one neighbor, which could skew spatial results.

The dependent variable and main predictor variables, PCPI, are obtained for 1970 and 2004 from the BEA Regional Economic Information System. PCPI for 2004 is deflated to 1970 dollars using the CPI deflator. PCPI change (Equation 12) is calculated as:

$$C_i = PCPI_i^{2004} \,/\, PCPI_i^{1970} * 100 \tag{12}$$

Where:

C_i is 9170-2004 PCPI change in area *i*

$PCPI_i^{2004}$ is 2004 PCPI in area *i*

$PCPI_i^{1970}$ is 1970 PCPI in area *i*

Industry specialization for the FIRE and Service sectors are calculated as Location Quotients at the 2-digit SIC level. The data are provided from the National Historic GIS and is originally from the 1970 County Business Patterns Survey. Location Quotients (Equation 13) are calculated as:

$$LQ_i^s = (e_i^s/e_i)/(E_I^s/E_I) \tag{13}$$

Where:

LQ_i^s is the Location Quotient for sector *s* in area *i*

e_i^s is employment in sector *s* in area *i*

e_i is total employment in area *i*

E_I^s is national employment in sector *s*

E_I is total national employment

Population comes from the 1970 Census of Population, and is provided by the NHGIS. The Urban-Rural Continuum is provided for 1974 (the earliest year available) from the USDA. Originally a score of 0-9, where 0 is the most populous and urban, and 9 is the least populous and most rural. The detailed definitions are shown in Table 3.

In order to allow for weighting by population, the Urban-Rural Continuum is reversed. Since the continuum is originally calculated at the county level, scores for Economic Areas and States are constructed as population weighted averages using the following formula (Equation 14):

Table 3: Urban-Rural Continuum Codes

Code	Description
	Metro counties:
0	Central counties of metro areas of 1 million population or more.
1	Fringe counties of metro areas of 1 million population or more.
2	Counties in metro areas of 250,000 to 1 million population.
3	Counties in metro areas of fewer than 250,000 population.
	Nonmetro counties:
4	Urban population of 20,000 or more, adjacent to a metro area.
5	Urban population of 20,000 or more, not adjacent to a metro area.
6	Urban population of 2,500 to 19,999, adjacent to a metro area.
7	Urban population of 2,500 to 19,999, not adjacent to a metro area.
8	Completely rural or less than 2,500 urban population, adjacent to a metro area.
9	Completely rural or less than 2,500 urban population, not adjacent to a metro area.

$$WR_I = \Sigma((P_i * R_i)/P_I)/n \tag{14}$$

Where:

WR_I is the weighted rurality score for area *I*

P_i is the population of county *i*

R_i is the rurality code for county *i*

$P_I$is the population for area *i*

Right to Work status in 1970 comes from the National Right to Work Legal Defense Foundation. For states and counties, where aggregation unit boundaries follow state lines, RTW status is coded as “0” for regions without RTW legislation in 1970, and “1” for those which had adopted RTW legislation. For EAs, which can cross state lines, RTW is accounted for by using the percentage of the EA population that lives in a Right to Work location. For example, if the entire EA fell within a RTW state, it would have a value of 1.0, while an EA where only half of the population lived in the RTW state, it would have a value of 0.50. The final variable, connectivity, is calculated as the distance from a weighted centroid to a completed Interstate Highway. Highway information is provided by the Federal Highway Administration, and is extracted from Figure 2 (provided) to a ArcGIS line file. For counties, a centroid is used. For states and Economic Areas, the mean center for the areas population is used to represent how close the population is to an interstate highway. To asses proximity, a multiple ring buffer at 15 km increments is constructed around the highway shapefile in ArcGIS. The buffers are spatially joined to the point centroids, and the centroids joined back to the polygons from which they were created.

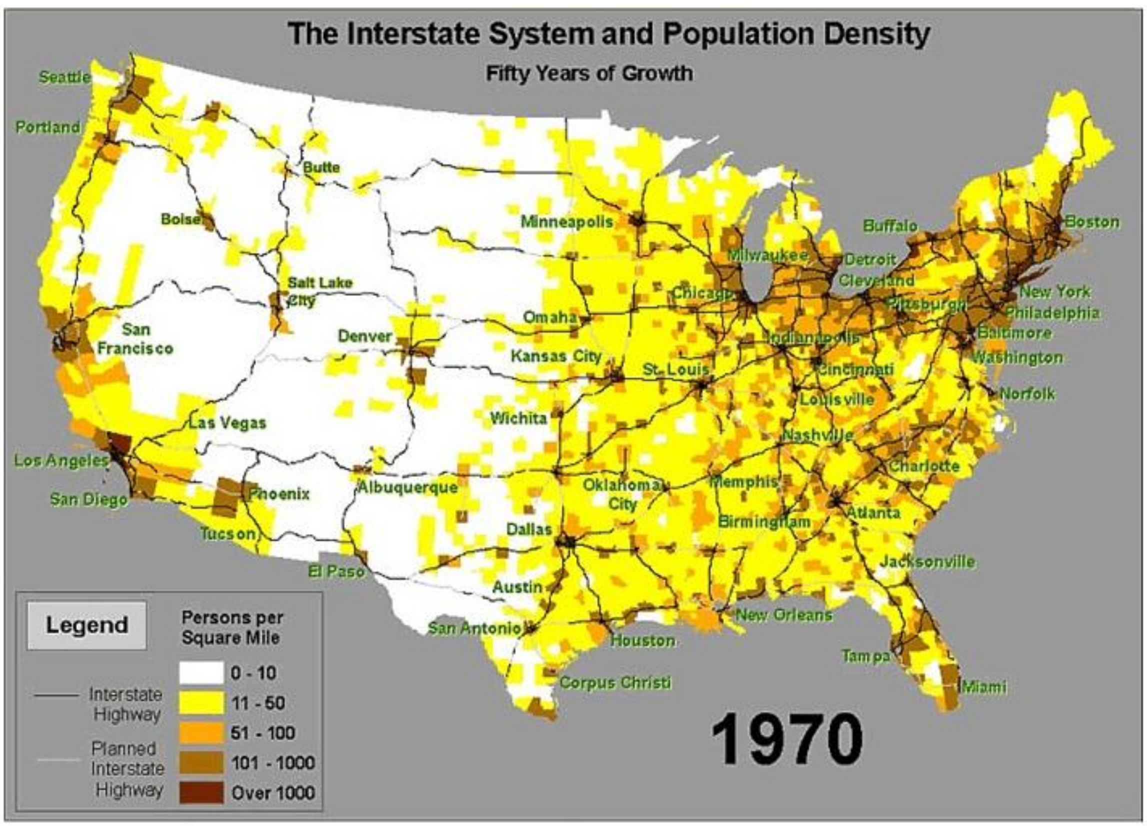

Figure 2: Interstate Highways in 1970
Source: Federal Highway Administration

Descriptive Statistics

Descriptive statistics are shown in Tables 4-6 for states, Economic Areas, and counties, respectively. The descriptive statistics tests are run in the NCSS statistical package from .dbf exports from the shapefiles. In general, the tables show exactly what is to be expected: with decreasing levels of aggregation there is greater variation than at higher levels of aggregation. This increase in variation already points to possible disparities in model fit.

The main predictor, 1970 PCPI has minimums, of $2,628, $1,971, and $1,330, with maximum values of $2,628, $5,174, and $26,443 for states, EAs, and counties,

Table 4: State Descriptive Statistics

	Min	Max	Mean	Std Dev	Shapiro-Wilk (p)	D'Agostino Kurtosis (p)
1970 PCPI	2628.00	5071.00	3835.76	607.17	0.97 (0.26)	-0.95 (0.34)
Change	146.92	212.56	178.04	14.74	0.98 (0.43)	-1.46 (0.14)
Population	332416.00	19953130.00	4125367.00	4343608.00	0.76 (0.00)	3.28 (0.00)
LQ Service	0.64	2.37	1.05	0.31	0.74 (0.00)	4.37 (0.00)
LQ FIRE	0.64	1.73	0.95	0.20	0.87 (0.00)	3.31 (0.00)
Buffer Distance	15.00	240.00	41.02	39.42	0.66 (0.00)	4.83 (0.00)
Right-to-Work	0.00	1.00	0.35	0.48	0.60 (0.00)	-7.97 (0)
Urban-Rural	0.00	900.00	26.07	128.47	0.19 (0.00)	6.34 (0.00)

Table 5: Economic Area Descriptive Statistics

	Min	Max	Mean	Std Dev	Shapiro-Wilk (p)	D'Agostino Kurtosis (p)
1970 PCPI	1971.00	5174.00	3525.26	554.11	0.99 (0.17)	0.55 (0.58)
Change	140.06	220.77	174.63	16.83	0.99 (0.51)	-0.95 (0.34)
Population	50747.00	20325400.00	1141790.00	2103352.00	0.45 (0.00)	8.90 (0.00)
LQ Service	0.52	2.39	0.99	0.27	0.868 (0.00)	5.90 (0.00)
LQ FIRE	0.44	2.05	0.86	0.24	0.94 (0.00)	3.76 (0.00)
Buffer Distance	15.00	195.00	41.02	44.12	0.65 (0.00)	4.71 (0.00)
Right-to-Work	0.00	100.00	36.67	46.18	0.66 (0.00)	41.48 (0.00)
Urban-Rural	5.25	900.00	47.94	74.31	0.37 (0.00)	9.91 (0.00)

Table 6: County Descriptive Statistics

	Min	Max	Mean	Std Dev	Shapiro-Wilk (p)	D'Agostino Kurtosis (p)
1970 PCPI	1330.00	26443.00	3259.86	964.82	0.70 (0.00)	36.68 (0.00)
Change	1.00	710.86	176.86	31.57	0.92 (0.00)	29.52 (0.00)
Population	164.00	7032080.00	65701.19	230328.00	0.22 (0.00)	38.96 (0.00)
LQ Service	0.00	4.67	0.83	0.47	0.89 (0.00)	21.45 (0.00)
LQ FIRE	0.00	16.18	0.74	0.73	0.44 (0.00)	36.49 (0.00)
Buffer Distance	0.00	285.00	56.27	42.61	0.86 (0.00)	12.17 (0.00)
Right-to-Work	0.00	1.00	0.39	0.49	0.62 (0.00)	112.00 (0.00)
Urban-Rural	0.00	9.00	5.95	2.53	0.90 (0.00)	-8.88 (0.00)

respectively. Already, there is an increasing range of values as aggregation size decreases. Interestingly, the standard deviation is larger for states than EAs, though counties have the largest range. This indicates that although the EAs have a larger range than states, most EAs are a bit closer to the mean than states. These distributional effects are confirmed when the kurtosis and skewness values are examined. States and EAs both pass the normality tests, although the state distribution is a bit flatter than EAs. Counties fail both tests, although that is largely driven by upper end outliers, notably Shawano and Menominee Counties in WI, who are wealthy but with small populations, and counties in the New York City, Sacramento, and Austin area. An interesting trend starts to emerge when 1970 PCPI is mapped in Figure 3. Although the statistical distribution is largely normal across scales, the spatial distribution is far from random. At all scales, a distinct regionalization of income is present, with New England, the Rust Belt, and California/Nevada representing concentrations of high income. These pockets of higher income are consistent with the expectations of higher income due to the urban and industrial concentrations of these areas. These urban forces are shown through the highest of the standard deviation outliers being present in the core urban areas of New York, Boston, and San Francisco, where there is an expected degree of price inflation, but also where these largest-of-the-large cities serve as the central places, and in turn, home of the highest order goods and services. When looking at the Rust Belt, the incomes are not as far away from the national mean. At the state level, Rust Belt incomes are within 1.5 standard deviations of the mean, but most are 0.50 standard deviation from the mean. At the smaller scales urban areas again the homes to the highest incomes, while the rural EAs and counties fall much closer to the national mean. The Southeast has a regional concentration of low incomes. Similar to the northeast and Rust Belt, the urban areas have slightly higher incomes than their rural neighbors, but in this case, the urban areas such as Atlanta, Charlotte, and Birmingham fall in line with the national mean and the rural areas fall below it. Such a pattern represents a large concentration of both poverty as well as the possibility for an urban wage premium in the region. These are further reinforced through a comparison of the rural areas in the Southeast to the rural areas in the Midwest and Plains States. Here, the rural areas in the Midwest and Plains generally fall close to the national mean, whereas the Southeast fall well below. This suggests that the low incomes in the Southeast are not solely a result of simple rurality, but of a regional effect as well. This concentration and regionalization sets the stage for two issues to be further explored in this dissertation: the presence of convergence, and the spatial dependence of the process.

The dependent variable, PCPI change ratio, ranges from 146.92-212.56 for states, 140.06-220.77 for EAs, and 80.62-710.86 for counties. Of immediate interest is the fact the minimum values for states and EAs do not fall below 100, indicating that no areal unit lost ground in the study period. For counties, the minimum value of 80.62 indicates that the worst performing county lost ground by about 20%. States and EAs have

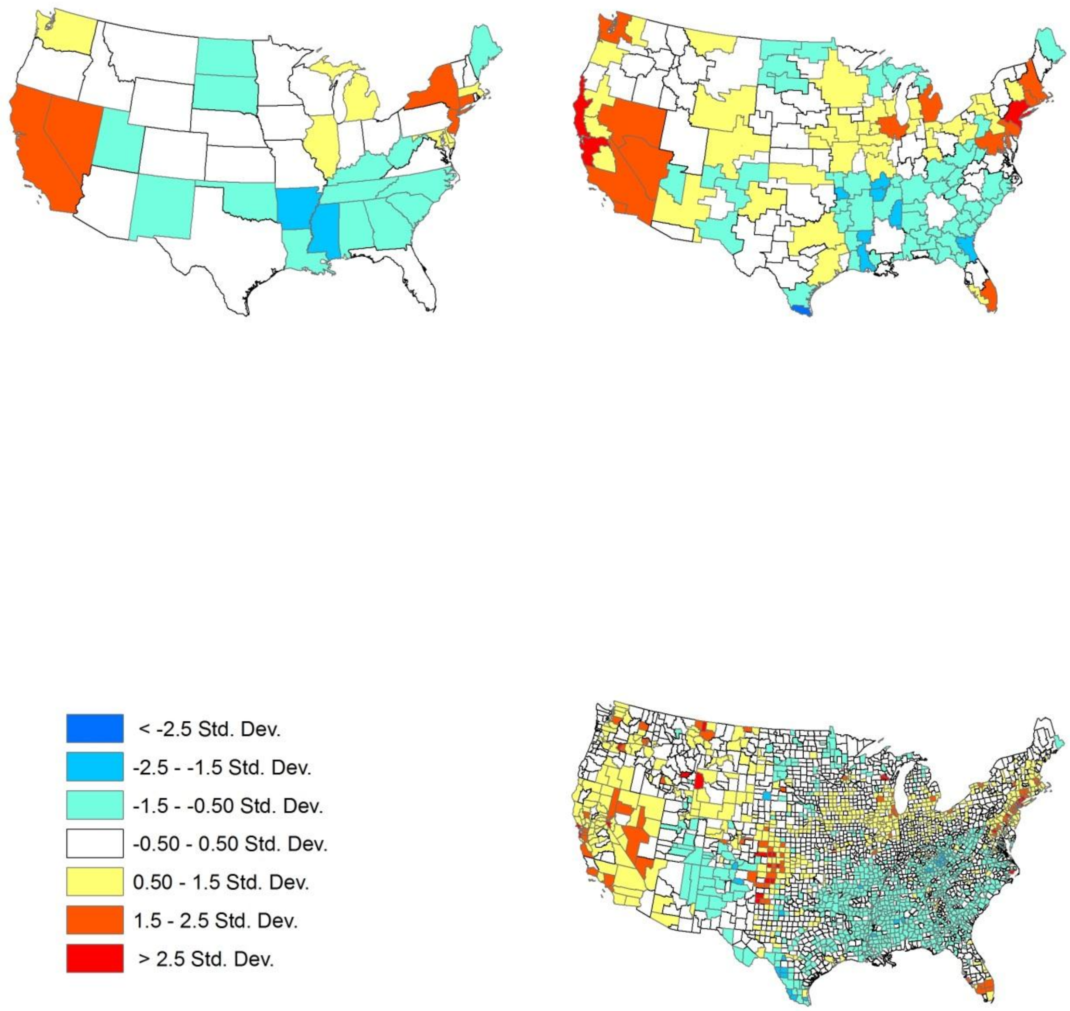

Figure 3: 1970 PCPI Standard Deviation Maps

minimum values that show that no region is worse off in terms of PCPI in 2004 than in 1970, indicating that even poor performing areas still exhibited growth. This is slightly different from what is indicated by the county distribution where some counties experienced a decline. This decline, however, is relatively small. Only 14 counties have a change value of less than 100, indicating that for a very large part, there was ubiquitous growth at the county level in this time period as well. Counties also have a much more extreme value on the high end of the distribution as well. The uppermost outlier (Loving County, TX) is a county that has a very low 1970 population but also experienced rapid investment due to an energy boom in the study period, raising the PCPI. But, this represents an important point about the smaller aggregations units in general: since they do not mask the data as much as the large levels they are more sensitive to outliers with extreme values. The maps in Figure 4 display a similar pattern to the 1970 PCPI in terms of regionalization. However, the actual values are inverted, with the fastest rates of growth in the Southeast and slower growth rates in the Rust Belt. This provides some suggestive evidence for the convergence process occurring, as it is that region of low initial values that grew the fastest.

Population is a unique variable in this study, since the larger units of aggregation have greater potential for larger values than the smaller units making a simple comparison of non-normalized values across scales difficult. The best way to compare values, then, is through the normality diagnostics. At no scale does population pass a normality tests. However, all scales fail the tests in the same manner, with positive values. Population distribution in 1970 is marked by a large number of low values,

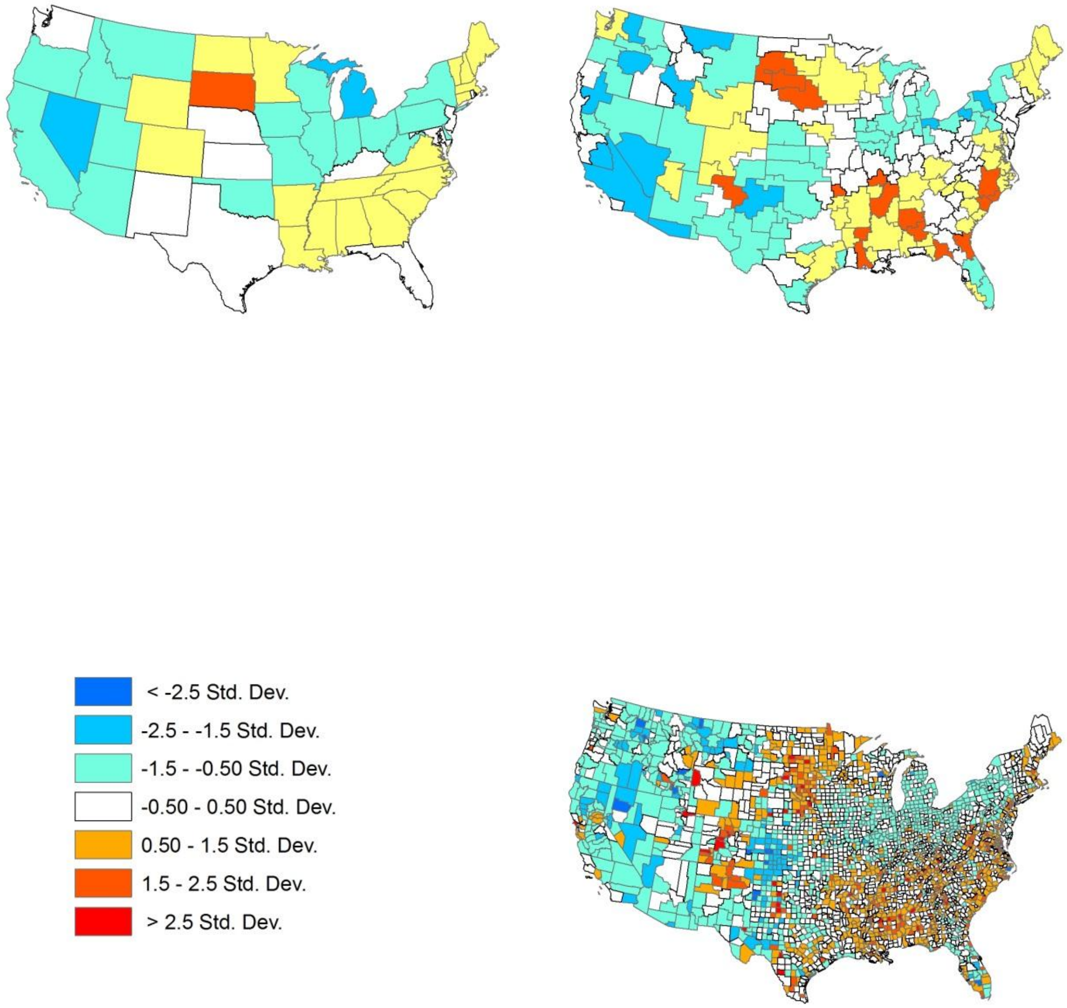

Figure 4: PCPI Change Standard Deviation Maps

with outliers of a great magnitude on the upper end. In other words, counties had a small number of relatively large population concentrations. In essence, people tend to cluster around each other, reflecting the importance of cities. In Figure 5, an interesting pattern is displayed where impact of the few large cities becomes even more pronounced. The state map shows a wide range of population values, with the sparsely populated Mountain and Plains States, and large values in the Rust Belt states, California, Florida, and Texas. So, many states fell in to categories far from the mean. Once the states are broken in to smaller levels of aggregation, it becomes apparent that it is only the largest of the cities in the country that are driving those end grouping classifications. The cities fall in to the high standard deviation categories as statistical outliers, and the rest of the EAs and counties within them are much closer to the mean.

The importance of cities and concentration of population in urban areas is reinforced with the descriptive statistics of the Urban-Rural Continuum, mapped in Figure 6. This variable has difficulty passing normality tests at all scales as well. In looking at the minimum values, states and counties both have values of less than 1, indicating there are some very rural places with very small populations (recall the continuum was reversed and weighted by population for states and EAs). The minimum value for the EAs is 5.25 indicating at this level of aggregation there is a greater degree of urbanization. This is unsurprising since every EA is centered around a city. However, when compared to the maximum value of 900, a value of 5.25 is still quite rural. The maximum value for states and EAs is 900, and for counties is 9. The 900 value is Washington, D.C., which is unique to itself since it is a one district area containing 100% of its own population, thus creating a large value. The individual counties with values of

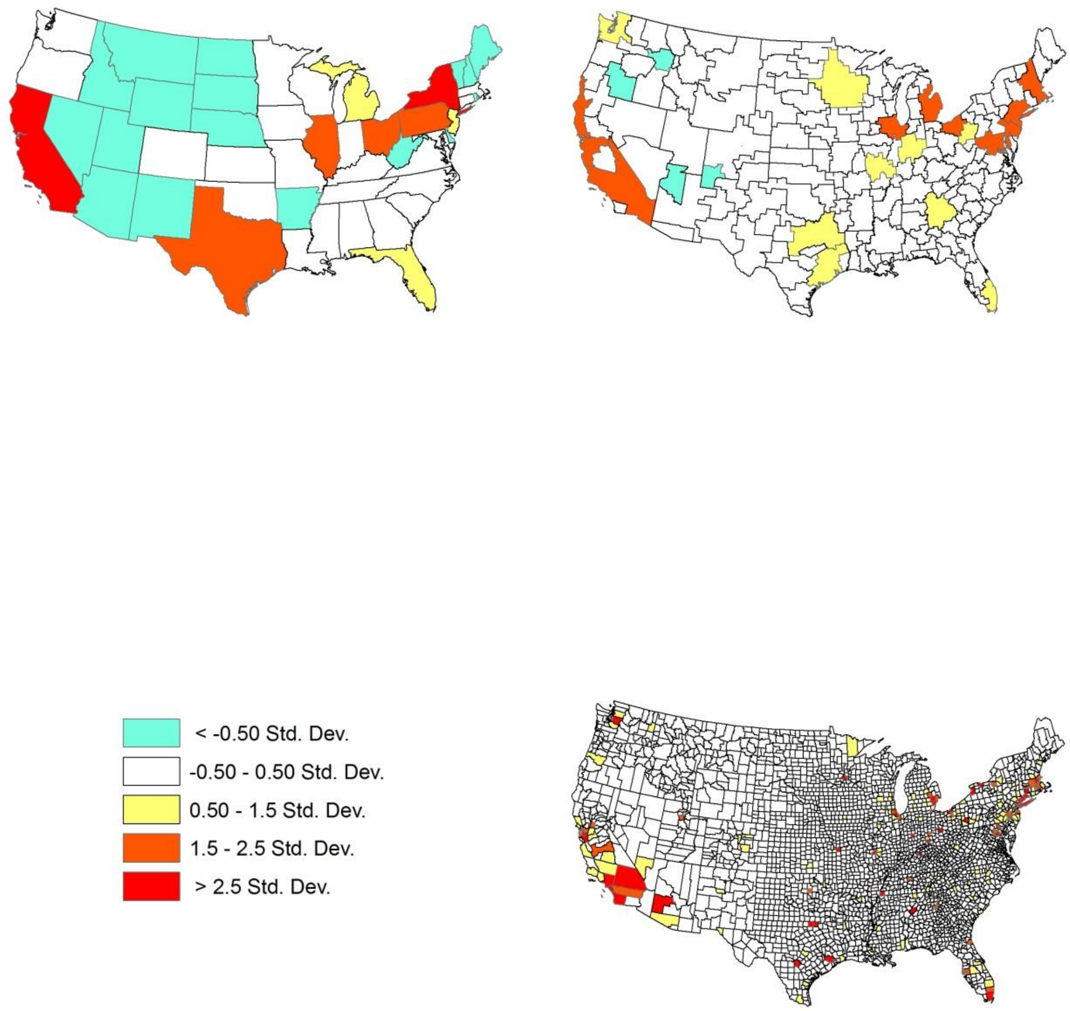

Figure 5: 1970 Population Standard Deviation Maps

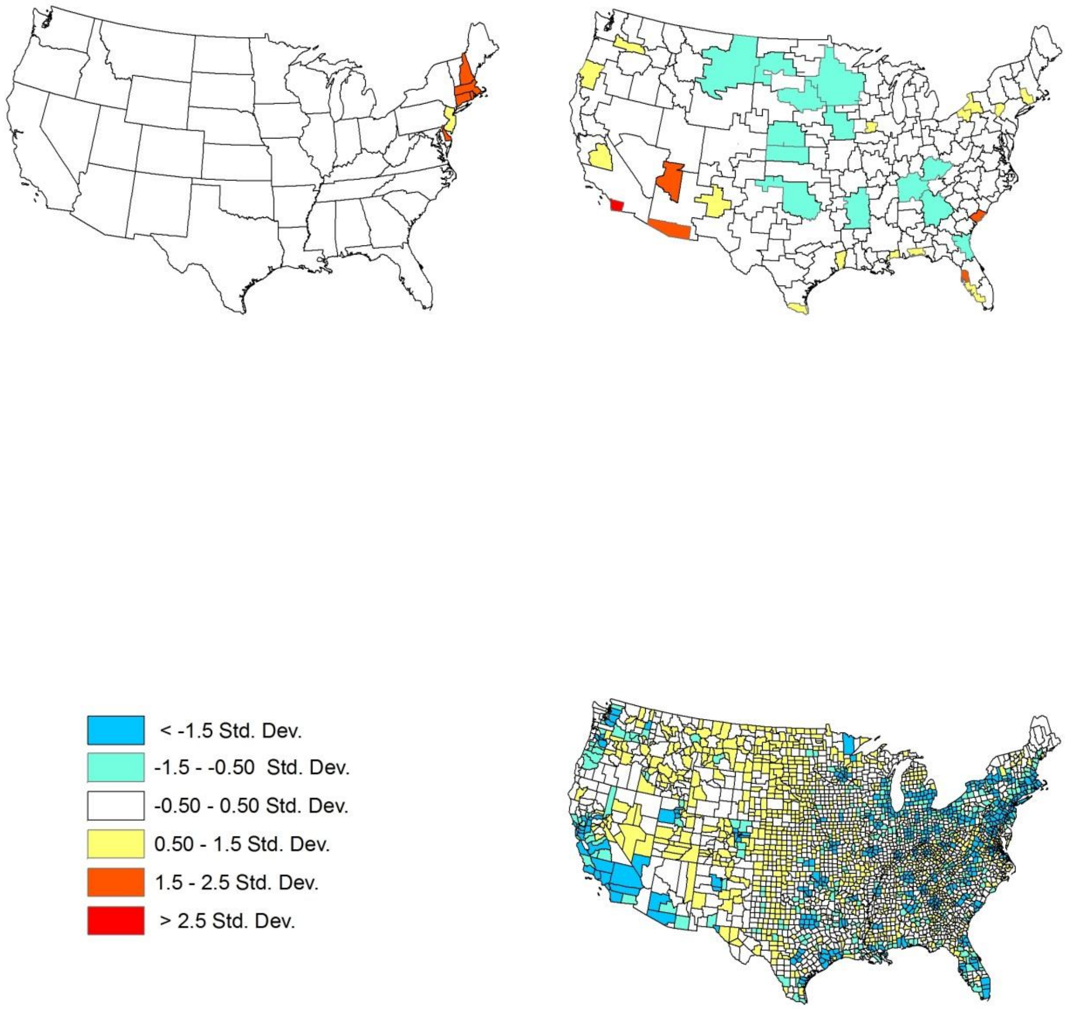

Figure 6: 1974 Urban-Rural Standard Deviation Maps

9 are the very urbanized ones, such as New York County, NY or Cook County, IL. The mean values for the weighted state and EAs are quite low, reinforcing the rurality of the country as a whole when we account for population. At the county level, the mean is at 5.65, indicating a mid-level of urbanity, but still a value that would fall in to the non-metropolitan category defined by the USDA. Similar to the raw population maps, Figure 6 shows the unequal distribution of urbanity. At the state level, the highest values are in the small states in New England, which is reflective of an ability of urban areas to dominate relatively small states. Most of the states fall within the mean range, as they are large enough to have substantial rural and urban populations. With EAs, similar to the statistical measures, most of the nation falls close to the mean as the functional units are constructed to contain a central place and its functional hinterland. Worth noting is how the largest of the EAs in terms of area tend to fall below the average value. This would indicate the ability of large hinterlands to increase the rurality of a functional area. For counties, the map displays exactly what we expect: the counties which house large cities are on the high end, and the more rural areas in the center of the country and southeast fall below the mean.

The LQ for the FIRE sector also follows the trend of increasing variation with decreases in scale. There is a minimum value of 0.64, in West Virginia, indicating a stark lack of specialization in that state. For EAs and counties, the minimum values decrease of 0.52 and 0.00, respectively. The maximum values for states, EAs, counties are 1.73, 2.05, and 16.18. These ranges should be expected and are consistent with the M.A.U.P. theory described previously. Interestingly, the mean values for each aggregation falls short of 1.0, the expected national mean. This suggests a concentration of the sector in a relative few number of places, with most regions falling below the expected. While it would be easy to simply dismiss that departure from the expected value of 1.0, such as the fact that Location Quotients are not weighted by total population, or the exclusion of Alaska and Hawaii skewed results, there are other more interesting possible explanations as well. First, the FIRE sector is one that benefits from agglomeration so, by its nature, there should be a clustering of activities. Second, and perhaps more importantly, this is an example of a zoning problem in the M.A.U.P. The FIRE sector provides enough service to meet the national employment under the assumption of the Location Quotient. However, due to the concentration of employment in a few places nationally, there are a few units of aggregation with very high values, but many units with values of less than 1.0, thus bringing down the average. The greater number of units importing FIRE, the lower the average should be, which is the case in the movement from states to EAs to counties. Further evidence of this concentration is shown in Figure 7. Here, areas with large positive standard deviations are relatively rare and in expected regions. For states and EAs, very high LQ values are located in New York, Nebraska, San Francisco, Miami, and Birmingham all of which are regional financial hubs. Surprisingly, Rust Belt and Southern states and EAs tended to fall below the national mean, indicating these sectors were underdeveloped in the regions theorized to have converged from both ends. At smaller scales, with EAs and counties, additional insight is gained. Here, in the urban areas in the Plains and western portions of the country, there are concentrations of FIRE employment. These are not the financial centers, but rather areas that experienced rapid population growth, suggesting the importance of the real estate component of FIRE at the smaller scale.

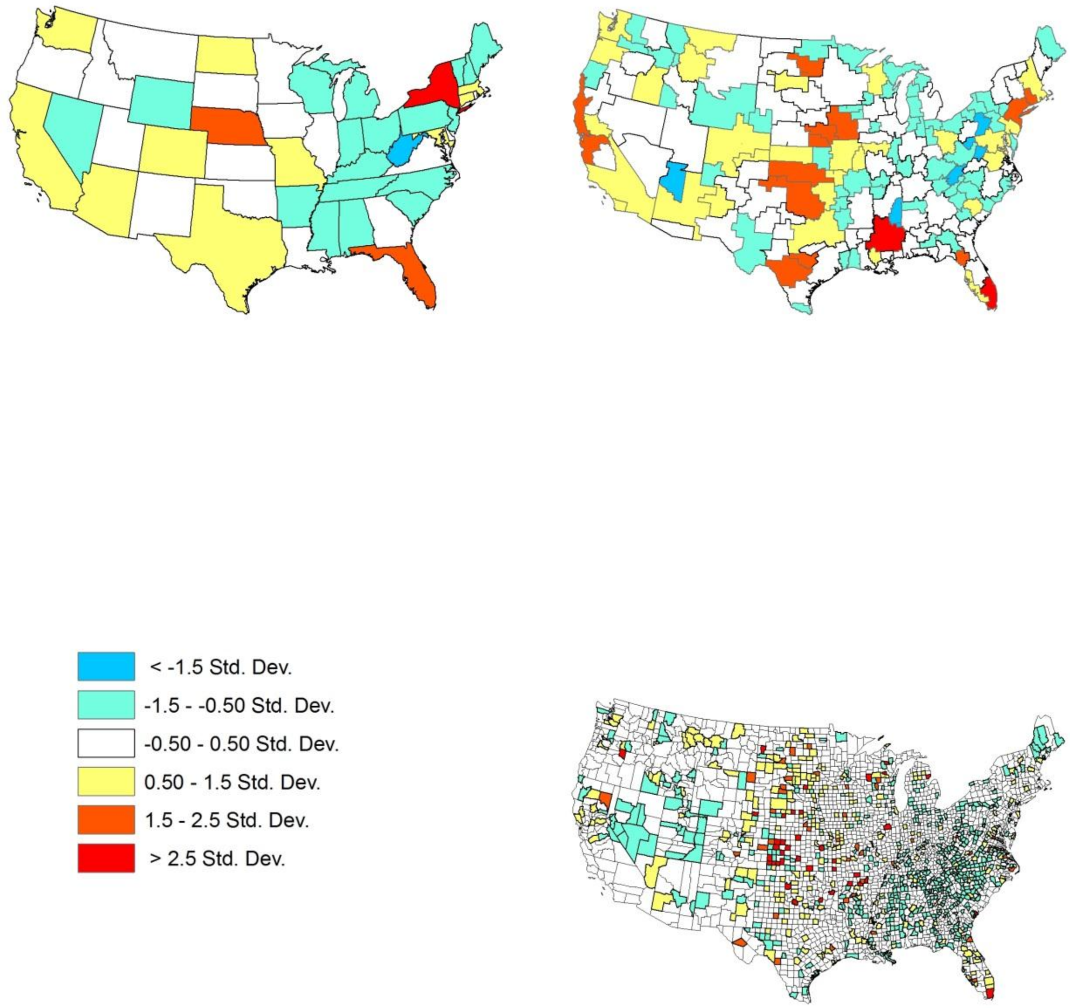

Figure 7: 1970 FIRE LQ Standard Deviation Maps

The Location Quotients for the Service sectors follow a similar pattern as FIRE. The minimum values also start at 0.64 for states, and move in a decreasing fashion as aggregation size decreases. Maximum values for Service sector specialization also have large values of 1.73 for states, 2.81 for EAs, and 4.67 for counties. This is similar to the FIRE distribution with some regions having very high concentrations, though not to the same degree. This is reflected by the mean values as well, as they are all much closed to the expected national average of 1.0. States and EAs, as the two largest units of aggregation are rather close to the expected mean with values of 1.05 and 0.99, respectively. Counties lag a little further behind at 0.83. This indicates a few things. First, the service sector is much more heterogeneous and seemingly more self-sufficient regardless of aggregation size versus FIRE. Outside of the smallest unit, anything with a functional economic unit in it should be self-sufficient in services. This would indicate that even with the broad 2-digit service classification used, the Location Quotients are still managing to pick up both higher order and lower order service concentration. This could be due to several factors, but most easily can be understood through Central Place Theory. There is a hierarchy of services (and goods) that are offered depending on the size of the market. Smaller markets offer lower order goods and services, and larger markets offer higher orders. The large market center provides the higher order goods and services to its hinterland comprised of smaller market centers. In this analysis, the larger units of analysis, EAs and states, are both comprised of the largest central places and the dependent hinterland. EAs simply have one, and states have several. Counties on the other hand, can be either core or hinterland. Examining the LQ mean reveals it is below 1.0, so most counties fall in to the hinterland category where they are importing some degree of services. In this case, it appears counties are offering lower order services, but higher order services still need to be imported form the larger Central Place. This is reflected in the maps displayed in Figure 8. At the state level, high specializations are present in New York, Nevada, the Southwest and Florida. These display a combination of factors due to the broad nature of the two digit classification. New York is the central place for the United States, and would offer the highest order services, as well as be a hub for business and professional services. For the western states and Florida, these are states that have a long legacy of tourism, so the service sector would play a large role there as well. This is a pattern that is reinforced with the EA distribution. In the EAs, as places with low service specializations, such as the Rust Belt and Southeast, remain low in the rural areas, but are in the expected range in their urban areas, reinforcing the importance of urban areas as central places. This is a pattern that is present in the county map as well.

Highway accessibility is an interesting case. In 1970, the Interstate Highway network was only partially completed. However, as noted in Figure 2, it is clear that places that received construction first were those important economic nodes and places of great population. As such, the units of aggregation where centroids were population was weighted display very similar statistics. For all units of aggregation, the minimum value was 15 km, indicating some units had highways running right through their center. The maximum values ranged from 240 km for states, 195 km for EAs, and 285 km for counties. Some of the more rural states, and their component EAs and counties in the western portion of the county, were quite a distance to a highway, which is not surprising given the region's sparse population and peripheral role in the economy. Average values

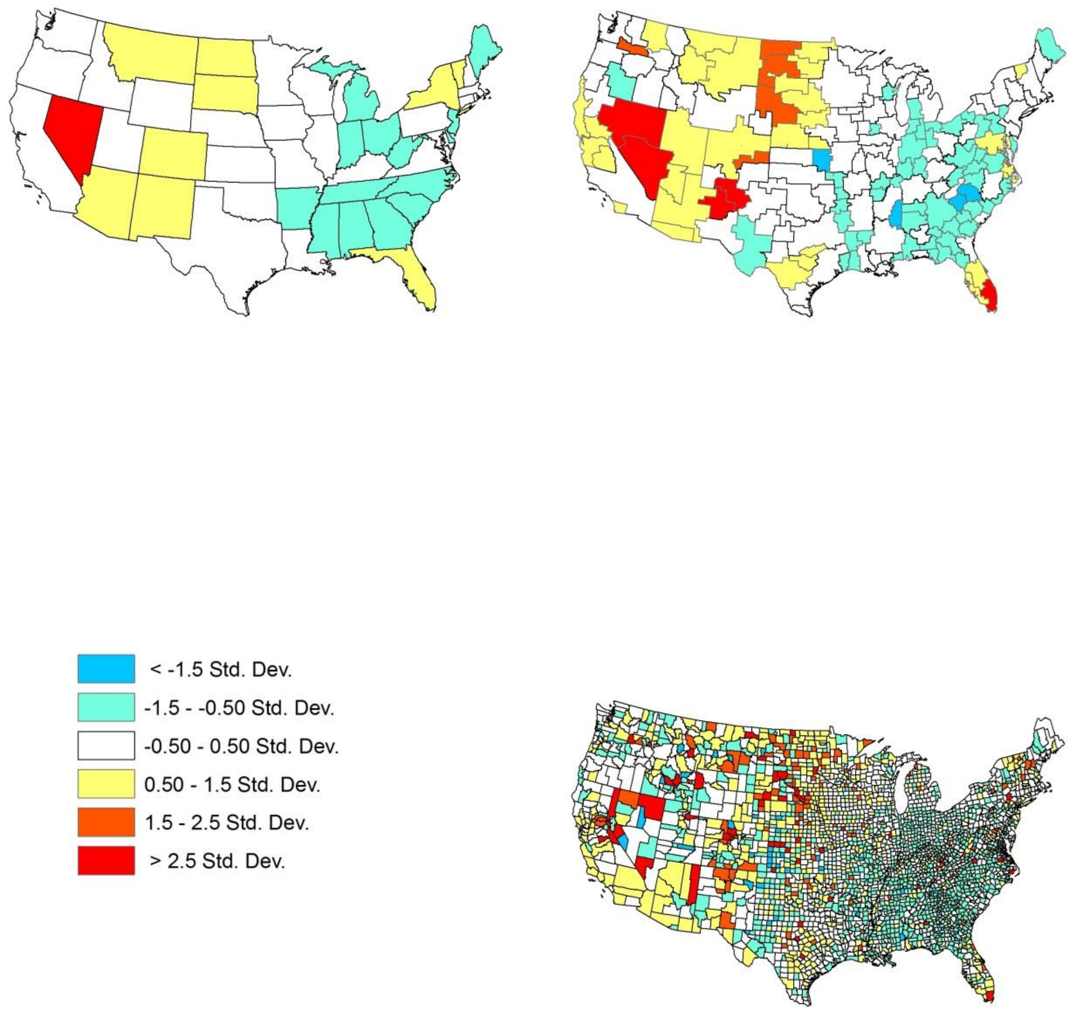

Figure 8: 1970 Service Location Quotient Standard Deviation Maps

for states and EAs are 42 km, indicating that for the population weighted larger units, most of the county was well connected to the transportation network. Counties, however, had a larger disparity, where more of them were further away from highway access. These, again, tended to be sparsely populated counties seen in Figure 5. This is reflected by their mean of 56 km. In terms of normality, the clustering of values towards the low end of the spectrum causes failure of normality tests across all levels of aggregation. The low end clustering becomes more pronounced when the maps in Figure 9 are examined. In all maps, there are a striking number of areal units that fall well below the average. The skewness of the variable across scales is supported with evidence from the maps in Figure 5. In all maps, there is a large presence of values below the mean, indicating that the mean is inflated by values quite far away. In other words, large portions of the country, regardless of scale, had good access to Interstates in 1970; however those that did not were quite far away. Generally, these regions of great distance are along the boundaries of the country in the west. In terms of pure access, the county map provides the best example due to the large, unweighted areal units used in the buffer. Here, the eastern portion of the country is quite well connected, with very few counties falling above the mean. This density of network is influenced by two key factors: the concentration of population in the eastern United States, and the concentration of economic activity in the eastern United States. In laying the interstate network, the earliest attention was given to the regions that needed to be connected first, which would be expected to be the largest places. This is further reflected in the central and western portions of the county. Here, the number of counties with great distance to a highway

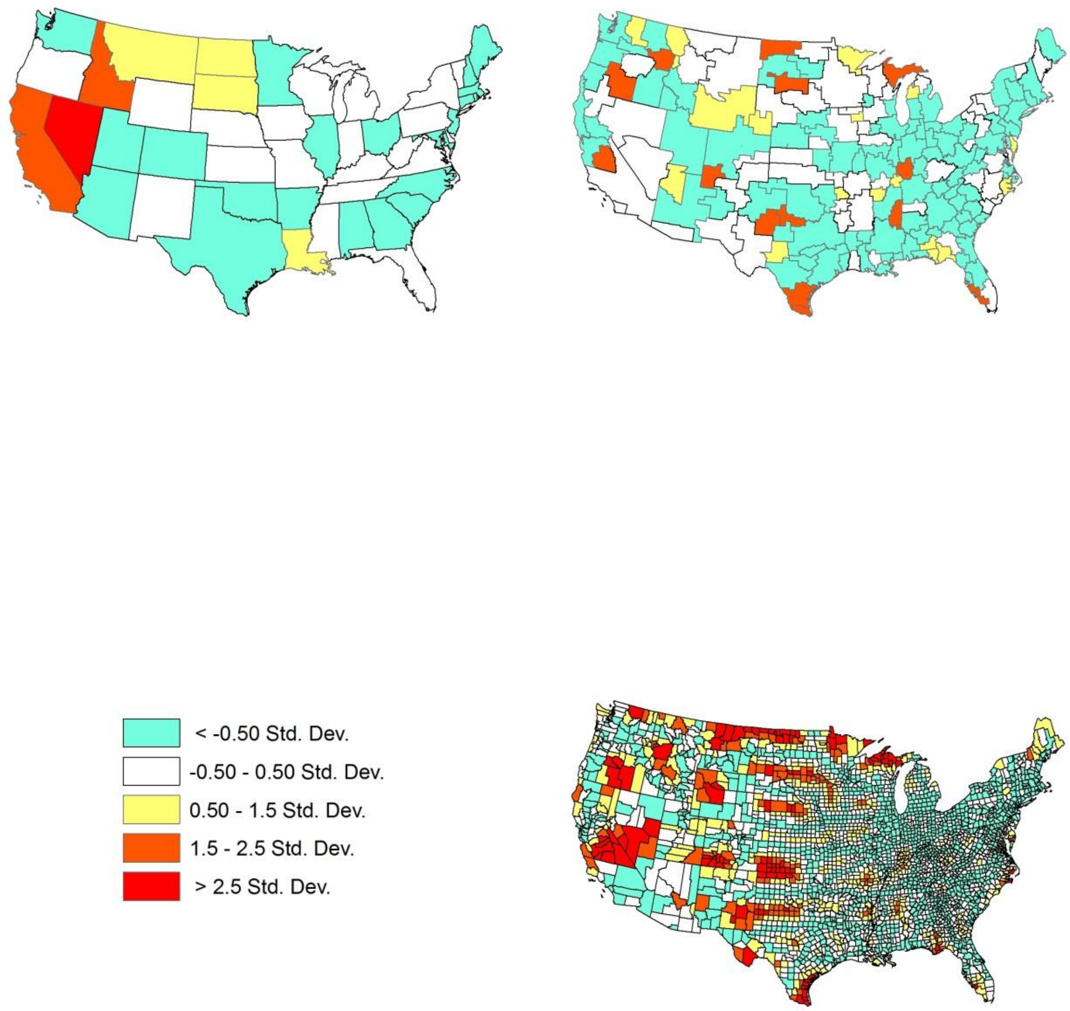

Figure 9: 1970 Buffer Distance Standard Deviation Maps

increased, but the cities in these regions that still had access. In the EA and state maps, a similar pattern emerges. In both of these maps, the centroids are population weighted. The attraction of population in highway construction is noticeable in these maps as the majority of the country falls in to classifications below or at the mean. Very few regions fall above it, but those that do are far above. Again, these are typically in the sparsely populated regions of the west. California is an interesting case. It is highly populated but has poor access according to the state map. This can be explained computationally, as California has a very long and narrow shape, with several population cores, thus creating a mean center that is not particularly close to anything.

The Right to Work variable is the only true dummy variable in the model. Most states, according to Figure 10, did not fall under Right to Work status in 1970. In fact, only 17 states had passed Right to Work legislation by the start of the study period, with a strong clustering of RTW states in the Southeast and Plains States. For counties, there is additional insight that about 36 percent of US counties fall in to RTW states. And from the EA adaption of the RTW variable, we see that roughly 36 percent of the US population are subject to RTW legislation. The maps for EAs and counties follow the state map quite well. Since the county map was a dummy, it perfectly follows the state map. For EAs, the distribution is roughly the same. In fact, the only reason it was not included as a dummy was because some EAs cross state lines. However, only a few cross state lines and account for a mixing of RTW and non-RTW populations. As such, the values tend to follow the RTW lines, as EAs within RTW states are at 100 percent, EAs in non-RTW states at 0 percent and those that split are in the middle.

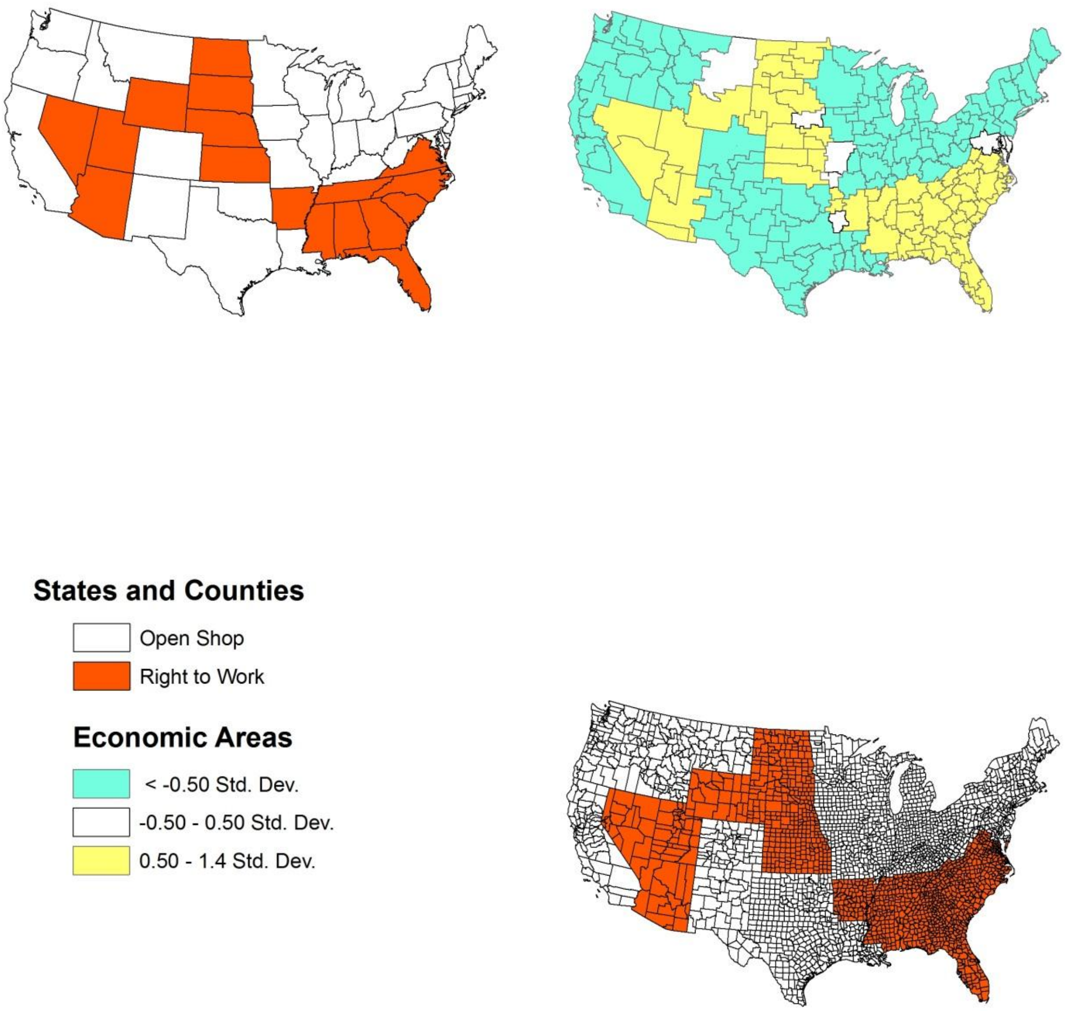

Figure 10: 1970 Right to Work Status Maps

Correlation Matrices

For each level of aggregation, a Pearson's correlation matrix is used to detect for multicolinearity among variables and to identify early relationships between the predictor variables and dependent variable. A quick glance over Tables 7-9 shows that none of the variables meet or cross the 0.7 threshold that indicates a multicolinearity problem if used together in a multiple regression. At the state level, the first evidence of beta convergence appears, with a negative correlation (-0.32) between 1970 PCPI and income change. Most of the other hypothesized predictors have a moderate relationship to income change, with absolute correlations between 0.1 and 0.4. Positive correlations are present for FIRE specialization, RTW status, and the Urban-Rural score. Although not the strongest relationships, these do fit with the theoretical base behind their inclusion: FIRE specialization represents localization benefits, RTW legislation is an incentive to new firms, and more urban places are the center for growth. Negative relationships are present between change and population, service specialization, and buffer distance. The relationship between buffer distance and change is the one most in line with theory. The service specialization is so small it is essentially a zero correlation and can be discounted, but population is interesting. Urbanization benefits should in theory have a positive.

Table 7: State Correlation Matrix

	1970 PCPI	Change	Population	LQ Service	LQ FIRE	Buffer Distance	Right-to-Work	Urban-Rural
1970 PCPI	1.00							
Change	-0.32	1.00						
Population	0.39	-0.34	1.00					
LQ Service	0.39	-0.03	-0.18	1.00				
LQ FIRE	0.46	0.10	0.20	0.52	1.00			
Buffer Distance	0.11	-0.40	-0.05	0.54	-0.06	1.00		
Right-to-Work	-0.42	0.28	-0.26	0.04	-0.08	0.11	1.00	
Urban-Rural	0.32	0.35	-0.13	0.53	0.56	-0.12	-0.14	1.00

Table 8: Economic Area Correlation Matrix

	1970 PCPI	Change	Population	LQ Service	LQ FIRE	Buffer Distance	Right-to-Work	Urban-Rural
1970 PCPI	1.00							
Change	-0.51	1.00						
Population	0.55	-0.07	1.00					
LQ Service	0.36	-0.10	0.04	1.00				
LQ FIRE	0.38	0.06	0.28	0.46	1.00			
Buffer Distance	-0.22	-0.01	-0.21	-0.01	-0.18	1.00		
Right-to-Work	-0.31	0.43	-0.18	-0.02	0.05	-0.01	1.00	
Urban-Rural	0.13	-0.08	-0.04	0.12	0.00	0.01	-0.01	1.00

Table 9: County Correlation Matrix

	1970 PCPI	Change	Population	LQ Service	LQ FIRE	Buffer Distance	Right-to-Work	Urban-Rural
1970 PCPI	1.00							
Change	-0.44	1.00						
Population	0.24	-0.05	1.00					
LQ Service	0.17	0.01	0.09	1.00				
LQ FIRE	0.14	-0.04	0.06	0.12	1.00			
Buffer Distance	-0.06	-0.02	-0.17	0.02	0.12	1.00		
Right-to-Work	-0.20	0.25	-0.10	-0.06	0.24	-0.40	1.00	
Urban-Rural	0.30	-0.08	0.40	0.09	-0.02	-0.39	-0.17	1.00

relationship with growth, thus reflecting a positive correlation between population and change. However, here it is negative. Possible explanations are that it is not just absolute population that matters, but urbanity as well, or that economic development is filtering down the urban hierarchy in the Rustbelt-Sunbelt transition. Another possibility is that smaller cities simply grew faster than larger ones. Either way, this is a result that warrants further examination in the conditional model.

Correlation coefficients for EAs should be smaller due to M.A.U.P., and for the most part, the correlation matrix follows this expectation. An interesting exception is the relationship between 1970 PCPI and change, which at -0.51 is a stronger relationship than at the state level. The other hypothesized predictor variables fall in line with M.A.U.P. theory as well as their bases for inclusion in the model. The correlation coefficients mostly dropped off to absolute values smaller than 0.10, with the notable exception of Right to Work status. As with states, it is positive and slightly larger. This increase, however, cannot be considered a true deviation from M.A.U.P. theory as the processing of RTW is slightly different at this scale than for states. The other positive predictor is the LQ for FIRE, which is consistent with the state results. The other variables have negative relationships. This is a slight departure from the state correlations that warrants further investigations: the Urban-Rural score is positive for states and could be a reflection of the filtering down process, at a smaller scale.

At the county level, the expected sign and relationship between change and 1970 PCPI is present, with a -0.44 correlation. Outside of the initial level of PCPI, the other only other variable showing much of a correlation to change is RTW status, with a positive 0.25 correlation indicating a relationship between a de facto wage ceiling and income change. The service specialization also had a positive relationship with change, indicating a localization impact at this level. What is interesting is that the county level of aggregation is the only level where the correlation is positive, indicating further investigation is needed in the confirmatory model. Also of interest is the sign change of correlation between FIRE and income change, as counties are the only level where this is a negative relationship. At this fine level of detail, it is possible to separate out the urban core from the hinterland of an urban area, and it may be that this is a reflection of the doughnut effect associated with urban growth in the post WWII economy.

Across scales, the correlation results provide a few things worth discussing and noting for further examination in the regression models. First, the strongest correlations are between the initial income levels and change. This provides suggestive evidence of beta convergence. The strength of the relationship is actually larger at the smaller scales, indicating that beta convergence is perhaps best studied at smaller scales. The largest of the correlation coefficients is for Economic Areas suggesting convergence to be a functional, not political process. The decrease in correlation coefficients across the board offers additional evidence of M.A.U.P. effects in convergence testing. However, all of these observations are preliminary; they need to be examined in the confirmatory analysis.

CHAPTER 5: EXPLORATORY SPATIAL DATA ANALYSIS

Purpose and Organization of Chapter

As discussed in the literature review, convergence is an inherently regional process. For there to be movement of capital investment from one region to another, definable regions must exist. And, in the case of convergence, these regions must be definable by their income levels. Regional processes such as these are typically not modeled well through OLS methodologies, since regionalization violates the assumption of independence among observations. This presents a problem for the traditional convergence test, an OLS regression. With the purpose of this dissertation examining the differences that spatial and scalar effects can have on beta convergence testing, spatial models must be constructed. The first step in the construction of a spatial model is to develop an understanding of the spatial structure of the variables of interest. For this dissertation, 1970 PCPI and PCPI change 1970-2004 serve as the main predictor and dependent variables. To gain an understanding of their spatial structures, Exploratory Spatial Data Analysis techniques are applied. Global and Local Moran's I (LISA) are applied using a first and second order queens weight matrix. This application should detect the extent of spatial influence at each scale, and how dependent that influence is on neighborhood definition. The LISA cluster analysis allows for the identification of converging regions, as well as providing the opportunity to identify potential additional predictors for the conditional convergence model.

The first portion of this chapter focuses on a first order analysis of 1970 PCPI at each scale. The global Moran's I will detect the presence of spatial autocorrelation of 1970 PCPI . If present, the Moran's I should be significant and positive. The local Moran's will identify the regional clusters of high income, low income, and income change. Regions that are cold spots are the regions of low incomes, which should be the regions of expected fast growth. Regional hot spots are the regions of initial high incomes which would be expected to grow more slowly over the study period.

Next, the first order tests are applied to PCPI change. Again, the global Moran's I will detect the presence of spatial autocorrelation. With change, the regionalization is again expected to be a positive value, although the individual regions should be inverted in the LISA cluster analysis. A region of rapid growth in the location of the initial PCPI cold spot would suggest convergence. This would indicate that the area of initial poverty transformed into a region of rapid growth. The second regional effect expected in the region of initial wealth. This should appear as either a cold spot, or a spot of no significance due to the slowing of the growth in the region.

The second section of this chapter applies the same tests to each level of aggregation, only using a second order neighborhood matrix. In this section the results are not only discussed on their own merit in the convergence debate, but also compared to the results from the first order neighborhood matrix. Through this comparison, the effect of neighborhood definition on spatial dependence detection and model results will become more apparent. In addition, the results of these tests allow for a comparison of across weight matrices to identify the appropriate weight matrix for modeling at each scale in addition to identifying the extent of spatial dependence in the key variables.

First Order Analysis

The first step in this analysis is to perform the global Moran's I test for 1970 PCPI. The results of this test are shown in Table 10 below. Here, the significant positive values fit with the hypothesis of a strong positive regional effect for initial income levels in the convergence process. The Global Moran's I value for states is 0.4578, EAs is 0.5034, and counties is 0.4548, all significant at 0.01 level. All of these fall near the 0.50 value, indicating a relatively strong association between the PCPI in an area and the PCPI of its neighbors. These results offer a slight departure from the expected results coming from M.A.U.P. theory, where the largest correlation should come at the largest level of aggregation. However, each of the units capture distinctly different processes. States are large enough where they include several different functional economies, and where neighbors might not share the same locational attributes. EAs are self-contained functional units, and counties are small enough where even a first order matrix will include neighbors that are within a functional unit and those that are not. So, EAs appear to be the only one of these units to offer a neighborhood where neighbors capture the same effects. Positive values indicate that the clustering is of similar values. This result offers some support for the convergence hypothesis, the need for a spatial modeling approach, and the earlier descriptive statistics.

Table 10: 1970 PCPI First Order Moran's I

	Moran's I	P-Value
State	0.46	0.01
Economic Area	0.50	0.01
County	0.45	0.01

For the convergence hypothesis, the first requirement for bottom up convergence to occur is in place. What is displayed are distinct regions of wealth and of poverty, which is the precondition for convergence to occur. After all, without this regionalization of income, there would be no reason for investment to move. Significant spatial autocorrelation indicates that PCPI may not be independent enough to fit OLS assumptions, indicating that a spatial model would be more appropriate. In the descriptive statistics, the standard deviation maps generally pointed to a region of lower incomes in the Southeast and a region of higher incomes in the Rust Belt and northeast. The significant Moran's I values indicate that these regional effects are indeed not random, and would thus be the result of a larger process. However, Moran's I still does not identify those regions as statistical hot and cold spots. Rather, it just provides evidence that they may exist.

In order to identify those regions, LISA clusters are displayed in Figure 11. The first noteworthy aspect of these maps is the strong positive spatial autocorrelation across all scales. There are very few spatial outliers (low-high, high-low). This further reinforces the uniformity of the regionalization in place. The regionalization that was noted in the standard deviation maps is also present in the LISA clusters with a large cold spot in the Southeast, and a region of high income in the Rust Belt and northeast, and a hot spot on the west coast. In the state map, the core of the hot spot in the northeast is centered on New York, Pennsylvania, Massachusetts, Connecticut, and Rhode Island. The western hot spot is centered on Oregon. Since these are centers of the clusters, the actual cluster extends out one neighbor. So, the western cluster also includes California and Washington, while the eastern cluster includes Ohio and Maryland. This

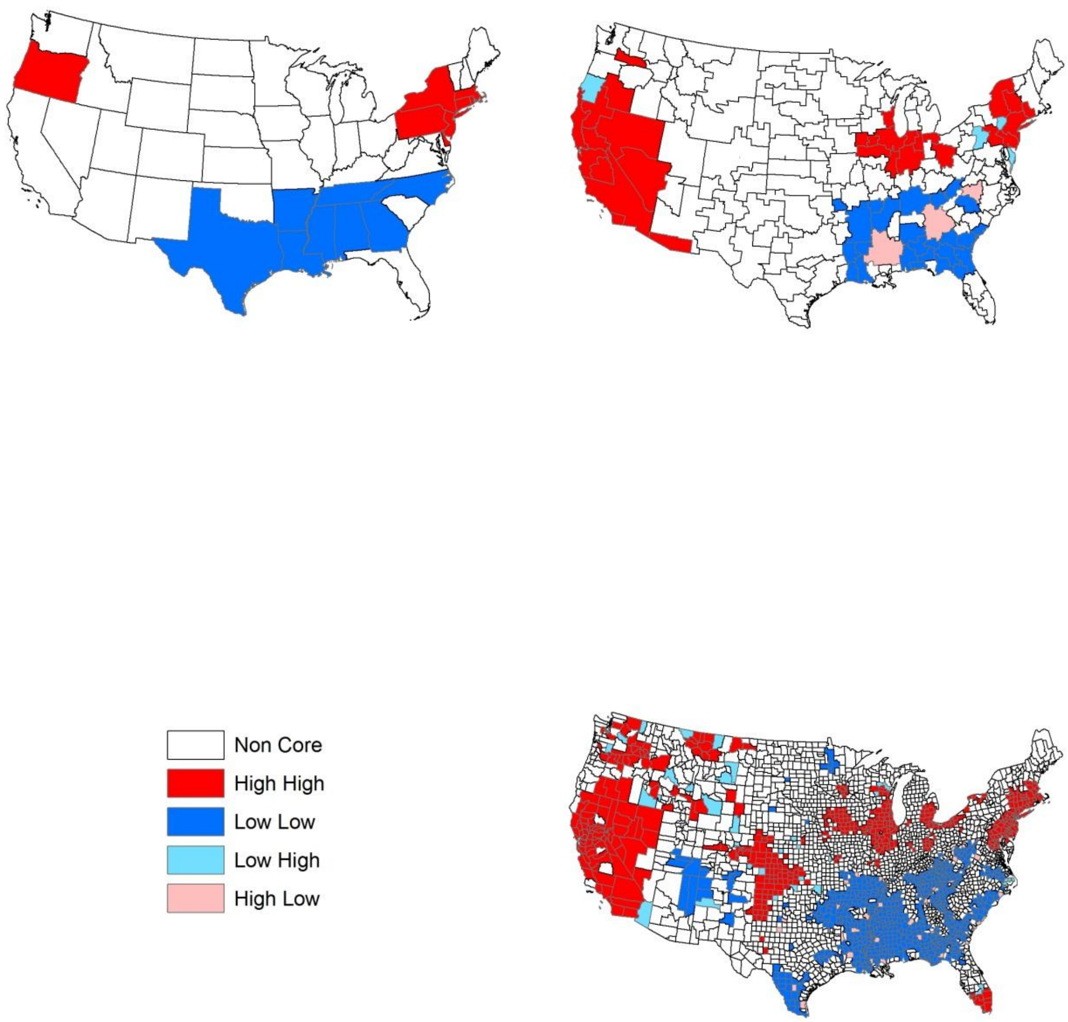

Figure 11: 1970 PCPI First Order LISA Clusters

of the fourth Kondratieff. The core around New England stretching to Ohio includes the heart of the Rust Belt. This is the old manufacturing region that was at the core of the industrial revolution and post-WWII manufacturing boom. Industries that were important in this region include steel, automobiles, and machinery. At the state level, the northeastern portion also includes upstate New York, which is home to a strong manufacturing core, as well as the high end service, technological, and financial centers of New York City and Boston. So, this cluster included both aspects driving the fourth wave of production, but also the high knowledge sectors characteristic of the fifth. Out west, the center around Oregon includes Washington, California, Nevada, and Idaho. This cluster includes the western manufacturing and service centers. In this area, the manufacturing center of California is included, as well as the major ports associated with Seattle and California. A strong service sector is also expected, as it includes the central places for the west such as Los Angeles, Seattle, Portland, and San Francisco, as well as tourism centered Las Vegas.

The region of low incomes is centered in the Southeast. Here, the core includes North Carolina, Georgia, Mississippi, Alabama, Louisiana, Arkansas, Tennessee, and Texas. This also extends out to include Kentucky, Virginia, West Virginia, and Oklahoma. Outside of the former Confederate states, this region includes two functionally different economies. In the more eastern portion, these are areas of historic poverty that were characterized plantation style agriculture, low levels of manufacturing, and poor transportation connectivity. Once industrialized, growth was centered on the textiles, tobacco, and furniture, with furniture and textiles drawn to the region through a filtering down process. The central region is characterized by low density population settlements, energy, and agricultural production. These are both regions that have seen growth during the study period benefitting from filtering down processs, the growth of the energy sector, and of a southerly population movement.

The smaller levels of aggregation add additional insight to the clusters in the maps. The clusters in the EA and county maps are largely consistent with the state level clusters. Both maps show there to be a large concentration of regional poverty in the Southeast and regional wealth in the northeast, west coast and Rust Belt. In particular, the west coast hot spot lines up quite well with the state maps, which may be a function of the relatively large counties in the region. However, the smaller level of aggregation allows for more refined clusters to be mapped in the east coast due to the smaller county size in the region. The first noticeable difference in these clusters is the presence of spatial outliers, especially at the EA level. Spatial outliers are present when the core of a cluster is disproportionally opposite to those values surrounding it. Notably, these are present in the southeastern cluster of low incomes in the EA map, with Birmingham, Atlanta, and Greensboro serving as islands of wealth in the poor region. These are all cities that are relatively equally spaced centers of production and consumption in the south. Greensboro was an old manufacturing and transportation center in North Carolina, Atlanta was the regional central place for the entire Southeast, and Birmingham was a steel and finance center in 1970. As these were the hubs of activity for the region, they would be home to the higher order goods and services, and should have higher levels of income. Thus, even in a regional cold spot, the importance urban areas as hubs are pronounced. This urban importance is reinforced in the county LISA cluster map. The Atlanta and Greensboro areas no longer serve as the cores to a cluster, and the home county of Birmingham is a high-low outlier. For Birmingham, the spread of the urban impact on income is relatively narrow, as even the suburban counties for Birmingham are the low outliers. For Atlanta and Greensboro the spread is more pronounced, as their regions are actually on par with the rest of the nation. This indicates that the urban effect is spread out enough, and the region large enough that they are able to be on par with the rest of the country and not be statistical outliers at this smallest scale. What is of interest here, however, is the impact of these spatial outliers in the southeastern region of poverty. The command and control centers in the region, the places that would be expected to have the highest incomes, were only on par with the rest of the nation, reinforcing the poverty in that region when examined at the county level.

The LISA maps at the smaller levels of aggregation also offer the ability to see which economies in a state are driving the clusters at the larger state level. For example, in the northeast and the Rust Belt, the county and EA maps show the hot spots to be very focused in the coastal area. The eastern seaboard along the Bo-Wash region is a hot spot of activity in the county and EA maps, which is consistent with the results of the state map. Here, the urban areas associated with this megalopolis appear to be the driving forces behind the strong state economies reflected in the state level hot spots. Also, additional hot spots in the Rust Belt are present along the Great Lakes, where a narrow hot spot stretches from Chicago to Cleveland. This band is present in the smaller aggregation maps, but not at the state level maps. This reflects the importance of the industrial region, as it incorporates the regional command center in Chicago, the glass and oil (Toledo), automotive (Detroit), and tool (Cleveland) centers of the region, as well as the importance of these places as access ports to the Midwest hinterlands to the Great

Lakes. Why these regions show up as the centers of hot spots in the region at these smaller levels instead of at the state level is likely reflective of the states they occupy. Outside of these urban cores, most of these states are largely rural. So, while the region is known as the center of manufacturing, that manufacturing was relatively concentrated in a few areas and was thus not able to inflate incomes enough to raise the state level PCPI in these areas to become a core themselves.

The southeastern cold spot identified at the state level also displays a greater degree of variability when examined at the EA and county levels. The presence of spatial outliers in the Southeast was already discussed, but the uniformity of the cold spot in the Southeast is not just broken up by the outliers of command centers. In addition to the spatial outliers of Atlanta, Birmingham, and Greensboro breaking up the monolithic cold spot in the Southeast, the EA map shows some initial signs of break up, as not every EA is a part of a core. At the county level this is further reflected through gaps in the I-65/I-75 Corridor, I-77 and I-85 in the Carolinas, and additional high-low outliers in urban core counties. This indicates that in places where there are certain attributes advantageous to economic growth, such as network access or urban effects, growth can occur even in places of poverty. However, similar to Atlanta and Greensboro, the large regional break ups of the southeastern cold spot are areas where the counties are non-core, indicating that these places of comparative wealth in the region simply are places that are on an even playing field with the rest of the nation. If the region were to converge, these would be places where further growth would be expected, as they would be the regional command centers.

Table 11 displays the global Moran’s I values for PCPI change. Similar to 1970

0.01 level. This is consistent with the expected results in a converging nation. The values at each level of aggregation are again positive, consistent with the theorized regionalization patterns with states having a Moran's I of 0.3718, EAs of 0.4843, and counties of 0.3442. Each of these is slightly less than the values of 1970 PCPI. This indicates that it was not a one-for-one relationship, where areal units in cluster of initial low incomes automatically became the members of a hotspot for growth. The implication, then, is that there is more to regional growth than investment flowing to regions with low wages. Interestingly, these values do not follow the expected variation in a M.A.U.P. analysis, with correlations decreasing as aggregation size decreases. Instead the best fit is again at the EA level. This provides some additional evidence that perhaps convergence is best studied at a functional level instead of a political one.

Table 11: PCPI Change First Order Moran's I

	Moran's I	P-Value
State	0.37	0.01
Economic Area	0.48	0.01
County	0.34	0.01

The LISA clusters for first order PCPI change are shown in Figure 12. Across scales there is again a strong regional effect with each map having notable clusters. These clusters fit with the regional expectations from the 1970 PCPI clusters maps and from the global Moran's I test for PCPI through a clear inversion of hot and cold spot locations from the 1970 PCPI maps. Instead of a cold spot in the Southeast and hot spots in the Rust Belt and western United States, the hot spot is in the southeast and cold spots are in the Rust Belt and western United States. However, as noted above, with the smaller Moran's I the clustering is not as tight. This is reflected through the slightly smaller extent of the clusters than in the 1970 maps.

The first noticeable region is the Southeast, a cold spot in the 1970 PCPI cluster map. In the PCPI change map the Southeast is a significant hot spot at all scales, fitting with the convergence hypothesis. For states, Virginia is included as a core, but Texas, Louisiana, Arkansas, and Alabama are dropped. This is somewhat surprising given the energy and financial boom that could be associated with Texas and Birmingham, AL. However, the energy boom only affected certain parts of Texas, Louisiana, Arkansas are generally outside the I-65/I-75 Corridor that opened that part of the south up to regional growth. In addition, that boom may have been short lived enough that it did not affect 2004 PCPI as strongly as one may expect. Further explanation can be gleaned from the EA cluster map. Here, the growth hot spot is actually slightly larger than the 1970 PCPI cold spot. For the Southeastern EA cluster, spatial dependence appears stronger, as holes in the 1970 cold spot are "filled" in the change cluster, and has also extend slightly westward. The "filling-in" effect is reflective of a greater concentration of growth in the region than of 1970 poverty. This is further reflected by continued growth of the high-low outliers in the 1970 map. In theory, those outliers should have disappeared, as the surrounding cold spots would have grown much faster. Rather, the high incomes in those outliers remain, giving the appearance that they served as growth centers for the region. This is supported by the standard deviation map of PCPI change in Chapter 4, where these urban areas were still at or above the national mean growth rate. Given their status as high-low outliers in 1970, that is not an expected result. The additional westward movement of the cluster extends in to the Louisiana and Arkansas region

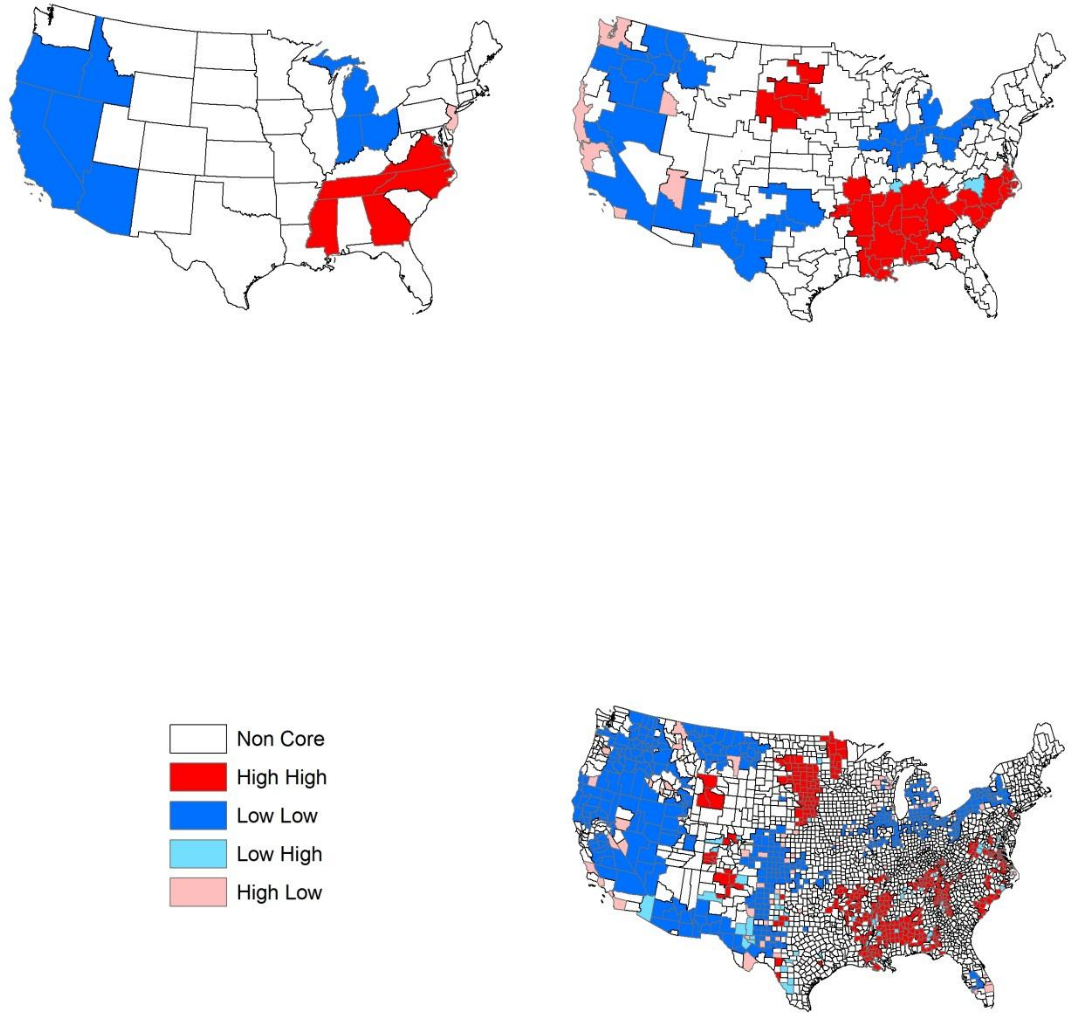

Figure 12: PCPI Change First Order LISA Clusters

that was left out of the state map. This indicates that growth extended to the eastern portion of the central Plains States, however not enough for those states to be considered clusters, thus allowing for Arkansas and Louisiana to be the center of a cluster, but at smaller levels of aggregation the EAs in Arkansas and Louisiana can be considered the cores of clusters.

The southern hotspot is slightly less pronounced in the county map, with individual counties that are generally in the deep south and the I-65 and I-75 Corridor. With the location in the deep south, the impact of low wages in one of the poorest regions of the country on growth rates can be seen. Here, a comparatively small growth in wages can equate to relative rapid growth as a percent change. In addition, the sparseness of the clusters indicates the difficulty in creating large scale uniform growth. The former core urban areas still grew according to the standard deviation maps.   But, the weaker Moran's I value is reflected through the slightly smaller extent of the clusters than in the 1970 maps, indicating growth did not spill out to the more peripheral areas. So, there appear to be several forces at play in explaining the growth of southern incomes. Rapid growth in the Deep South can be associated with the initial low incomes. However, urban areas also appear to draw growth in the south. The former spatial outliers manage to grow quickly despite their initial wealth, though not enough to create a cluster in the county maps. This urban growth continued, as other urban areas drew growth in the county maps, and the EAs all showed growth. The implication is that the growth associated with the urban areas may be very concentrated, and not fully spilling out into hinterlands.

Cold spots are found in the Rust Belt and western United States. As high-high clusters of 1970 PCPI, this is fitting with the convergence expectation. At the state level, the core of the Rust Belt cold spot moved westward to be centered on Ohio, Indiana, and Michigan. Without further analysis, this may appear surprising, as the eastern portion of the Rust Belt was home to some of the industries that were first to filter down to other regions. But, the EA and county LISA cluster maps offer a possible explanation. In both cluster maps, the Rust Belt cold spot is present; however it has a very distinct location. This cold spot is located in the same region of the Rust Belt that was the hot spot in 1970; the area bordering the Great Lakes. Areas such as Detroit, Cleveland, Akron, Buffalo, and Gary displayed slower growth. This is exactly what would be expected: some areas of very high manufacturing specialization in industries associated with the fourth wave were either rendered obsolete or filtered down to other regions. In fact, in the more rural states, such as Indiana and Illinois, the slow growth of the manufacturing core spilled over to include portions of the hinterlands of those urban cores. So, in a sense, the deindustrialization and poverty spread out from the deindustrializing core. This would cause the more rural states in the Rust Belt to be included in this core, as there was no region of growth to balance out the decline of the Great Lake region. This is in contrast to what was seen in the 1970 PCPI map, where the wealth in the manufacturing region was not able to move some of the states in to hot spot clusters. So, in terms of magnitude, the slow growth of the urban areas in the Rust Belt was stark when compared to their relative wealth in 1970.

An opposite effect can be seen in New York, where upstate is still characterized as a cold spot. However, New York City managed enough growth to keep the state from being a cold spot in the state map. This is a bit of a break from convergence theory, as

New York City in 1970 was a part of a cluster of high incomes, which would suggest it to be a region with a great likelihood of being a cold spot of change. However, it did not grow any slower that the rest of the county, indicating that there is something in New York that shielded it from top down convergence. Given that New York is the central place for the United States economy, it offers some evidence that its urbanity offers that refuge, a supposition that would need to be tested in confirmatory model.

Out west the cold spot encompasses California, Oregon, Nevada, Idaho, and Arizona. This is also consistent with the convergence expectation as there is a hot spot centered on Oregon in the 1970 PCPI map. Unlike the other regions, this cluster is larger than the 1970 PCPI cluster. The EA and county maps also show a degree of expansion of the cold spot. In the smaller scale maps, an interesting pattern begins to emerge in that the urban areas, especially in the EA map, are the urban centers of the region and are high-low spatial outliers. This indicates that the urban areas in the western region tended to grow faster than the rest of the country, whereas their surrounding counties and EAs displayed slower growth. This translates at the state level to cold spot classifications as only a small portion of the state experienced growth. This pattern of spatial outliers offers further evidence for the importance of urban effects in growth. In the south, the urban cores continued to grow in the bottom up convergence. The top down convergence in Rust Belt had urban areas drive state level classification, New York City shielded New York State, and the urban centers of the Great Lakes drive the state level classification in the rest of the cluster.

The first order analysis offers several bits of insight to the convergence analysis. First, it confirms spatial autocorrelation on the dependent and main predictor variables in the beta convergence model reinforcing the importance of accounting for space in formal convergence tests. Next, the regionalization of the main variables in the model is shown to be consistent with what is known about regional growth in the United States--deindustrialization in the northeast and rapid growth in the southeast. This indicates that the United States may very well have experienced a portion of the convergence process, and is thus a good study area for a formal test of beta convergence and spatial effects. Finally, the importance of a few other predictor variables begin to emerge. The most prominent of these is the role of urban effects, as command and control centers play the role of spatial outliers in both 1970 PCPI and PCPI change LISA cluster maps. Transportation access also appears to be of importance as regions in the I-65/I-75 corridor experienced some of the fastest growth.

Second Order Analysis

To add to the first order analysis, the Global Moran's I and local LISA tests are run on the same variables, but with a second order neighborhood serving as the spatial weight matrix. In the second order analysis, neighbors are not defined as those who share a boundary, but rather are those areal units who are separated by one unit. Second order models capture larger regional processes than first order ones, as it is not the neighbors, but the neighbors' neighbors that are exerting influence. For the purposes of this chapter, the goal is to apply this second order spatial weight matrix and compare results to the first order to identify which weight matrix will captures the greatest degree of spatial dependence. This will allow for the proper calibration of the confirmatory models.

For 1970 PCPI, the Global Moran's I results are similar to the first order results with the presence of positive spatial autocorrelation. Table 12 displays the results, which are notably weaker than the first order results. The value for states is 0.153, EAs is 0.3044, and counties is 0.3317. EAs and counties are significant at the 0.01 level, and states only at the 0.05 level. Positive values are indicative of clustering of values of similar magnitude and direction among neighbors, and the significant p-values statistical significance. However, the decrease in absolute value for each of the Moran's I statistics reflects a weaker relationship between second order neighbors than first order neighbors, especially at the state level where the p-value is not significant at the most stringent confidence level. Also worth noting is that the areal unit with strongest spatial autocorrelation is no longer the EA, but the county for the second order neighborhood. This suggests that the spatial dependence inherent in convergence is actually a fairly localized phenomenon, although county and EA values are close. At the larger scales, there is enough distance between neighbors where the similarities begin to break apart. Counties, however, are still small and close enough where second order neighbors can be in a functional economic region, and thus capture the same effects.

The LISA maps for 1970 PCPI are displayed in Figure 13. As expected, there is a smaller degree of regional clustering, though the clusters tend to be in the same general locations as in the first order analysis. There is a large cold spot in the southeast, a hot

Table 12: 1970 PCPI Second Order Moran's I

	Moran's I	P-Value
State	0.15	0.04
Economic Area	0.30	0.01
County	0.33	0.01

spot in the northeast/Rust Belt, and a hot spot out west. At the state level, the core of the Rust Belt hot spot is Ohio, whose second order neighbors include Illinois and New York thus capturing a somewhat smaller Rust Belt than the first order analysis. The northeastern cluster is centered on New Hampshire, whose second order neighbors include Connecticut, Rhode Island, and New York. This region is also present in the EA and county maps. For EAs, there is a clear distinction between the Rust Belt and northeastern core, with the Rust Belt core focused on Chicago and Central Indiana, whose neighbors will stretch to include central Ohio. The northeastern cluster contains most of New York, whose neighbors will include the Boston region and stretch to meet up with the Rust Belt centered around Cleveland. The county cluster is more broken up. There is the Midwestern component focused around Chicago, Detroit, and northern Ohio, but upstate New York is largely absent, removing that connection. Also, the northeastern cluster is largely focused on the Bo-Wash region.

The southeastern cold spot in the first order analysis is also present in the second order maps; however the results are slightly different than expected at the smaller scales. At the state level, the cluster has a core of Alabama, Georgia, and Louisiana , excluding such traditionally southern states of North Carolina, Tennessee and creating a smaller cold spot than in the first order analysis. However, with EAs and counties, the cold spot actually increases in expanse. This is somewhat surprising given the decrease in the Global Moran's I. However, in both of these maps, the cores of the regions are the same, there are just additional units on the perimeter. This can be explained through the magnitude of regional poverty. With the decrease in the Global value, the relationships are not generally as strong. Thus, it does not take as much of a similarity to create a

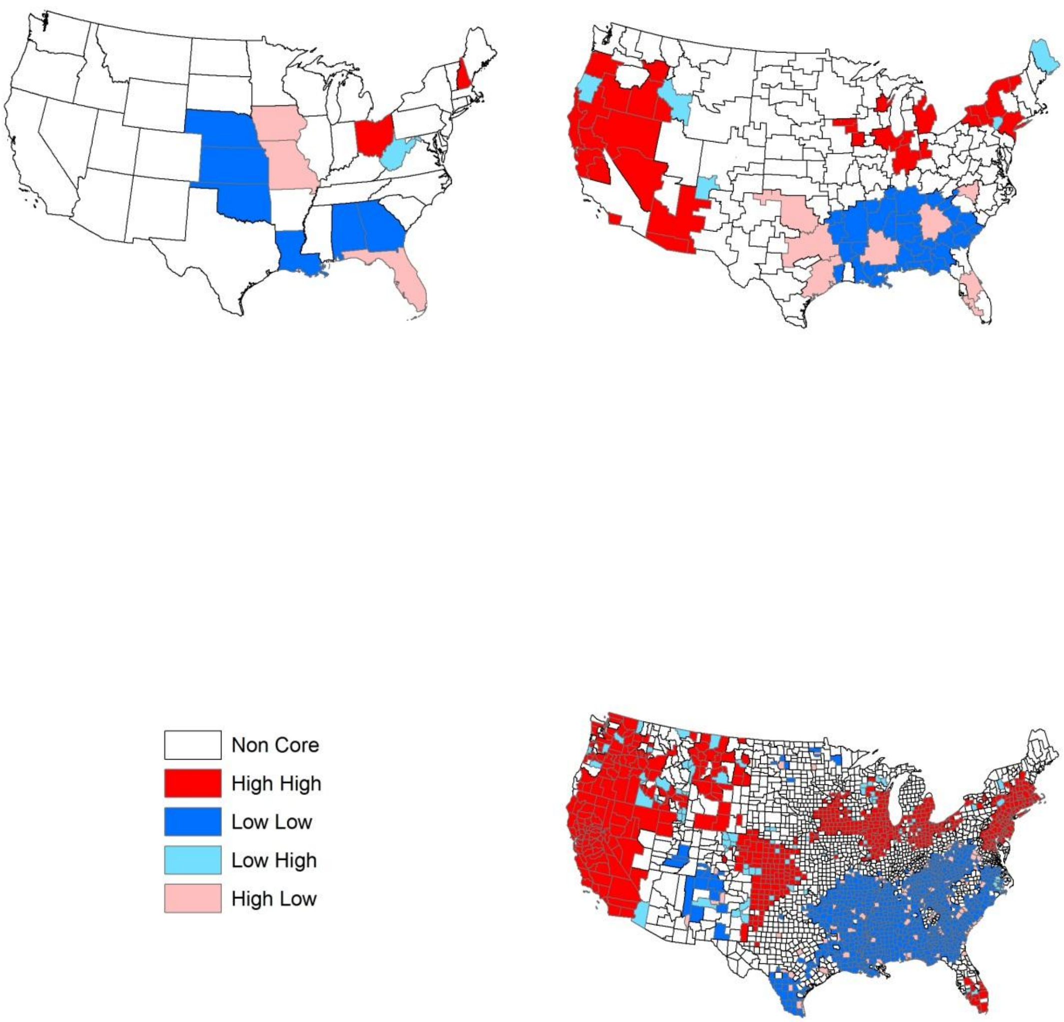

Figure 13: 1970 PCPI Second Order LISA Clusters

cluster.

The western hot spot is also an interesting case in the second order analysis. At the state level, there are no hot spots. This, again, can be explained by the states themselves, as their large size renders second order neighbors essentially useless for measuring spatial processes. This is in contrast to the evidence at smaller scales, where there are hot spots including most of California, Oregon, Washington, and Nevada. These results offer some additional insight as to the type of spatial dependence and economic structure of the region, where the forces driving growth in the region are very concentrated, especially west of the Rockies. The inclusion of the second order neighbors, thusly, eliminated any clusters at the state level, as the second order neighbors of even the coastal states include the Mountain and Plains States, region that are fundamentally different in economic structure. At the smaller scales, the EA cluster is focused around central California and extends to include parts of Oregon and Nevada. Again, with second order neighbors, this includes most of the region that was included in the first order maps. A similar pattern emerges in the county map, although the cores extend slightly further north. So, in general, the second order maps at the smaller scales cover the same area while the state map result is absent. This serves as a classic example of how aggregation size can yield different results.

The second order global Moran’s I for PCPI change offers some of the weakest evidence for regional effects in convergence. Consistent with the first order analysis, the global values for change are smaller than for 1970 PCPI. In fact, this test offers the weakest evidence for spatial dependence out of all of the global tests. Results are displayed in Table 13. The most noticeable result is the surprisingly small result for the state level test. The value of 0.0629 is only significant at the weakest 0.10 level. EAs return at 0.3097 and counties at 0.2852, both significant at the 0.01 level. As with all other global values the results are positive, indicating that the values for change are clusters in neighborhoods of similar values, albeit marginally in the case of states. Here, the weaker values add further weight to the idea that the regionalization of PCPI and in turn convergence is a relatively localized, yet regional, process. The larger regionalization is reflected by the large regional clusters in the PCPI map. However, within those regions, there is actually a great degree of variability. This is reflected by both the weakening of global Moran's I values in change and PCPI as the neighborhood size increases, as well as the decrease in the size of some LISA clusters. In this particular case, the weakening of change is quite stark. Already from the first order analysis change is shown to be less spatially dependent, indicating it is more than just the presence in a region that helps drive growth. When the region is an exceptionally large one, such as second order states, it crosses a threshold where regional effects diminish to the point where they are essentially useless in explaining growth. Even at the smaller levels, significance is still weaker than among first order neighbors, indicating that the regional effect decays relatively quickly.

Table 13: PCPI Change Second Order Moran's I

	Moran's I	P-Value
State	0.06	0.08
Economic Area	0.31	0.01
County	0.29	0.01

The second order LISA clusters in Figure 14 offer support to the comparative weakness of the spatial effects at this neighborhood definition. At the state level, the clusters are relatively few, which is to be expected given the weakness of the global Moran's I. In general, however, the clusters that do appear are consistent with the clusters of both the first order change analysis, but also the expected clusters for the 1970 PCPI LISA maps. The southeastern cluster of rapid change is present and centered on South Carolina, whose neighbors include Virginia, Kentucky, Tennessee, and Alabama. There is also a low-high cluster centered on Florida that indicates Tennessee and Mississippi to be states of rapid growth. This southern cluster is additionally present in the smaller scale analyses. As is the case in the 1970 PCPI maps, the smaller scale maps both show an expansion of the Southeastern region, indicating the same processes that caused the expansion of the 1970 PCPI were also in place for the PCPI change, providing evidence of convergence.

In the Rust Belt, the expected cold spot is not present in the state map. Applying the analysis to the EA and county maps, it becomes a bit more apparent as to why that is the case. The initial hot spot, and in turn region of relatively slow change is clustered around the Great Lakes, as shown in the smaller scale maps. When aggregated up to states, it becomes difficult to create a core that includes states that both bordered on the Great Lakes and had enough of their economy focused on that level of manufacturing to create a cluster. The clusters that are present in the smaller scale maps are consistent with expectations, focusing on the industrial regions along the Great Lakes. Consistent with the smaller clusters at the state level of aggregation, the expected low-low cluster

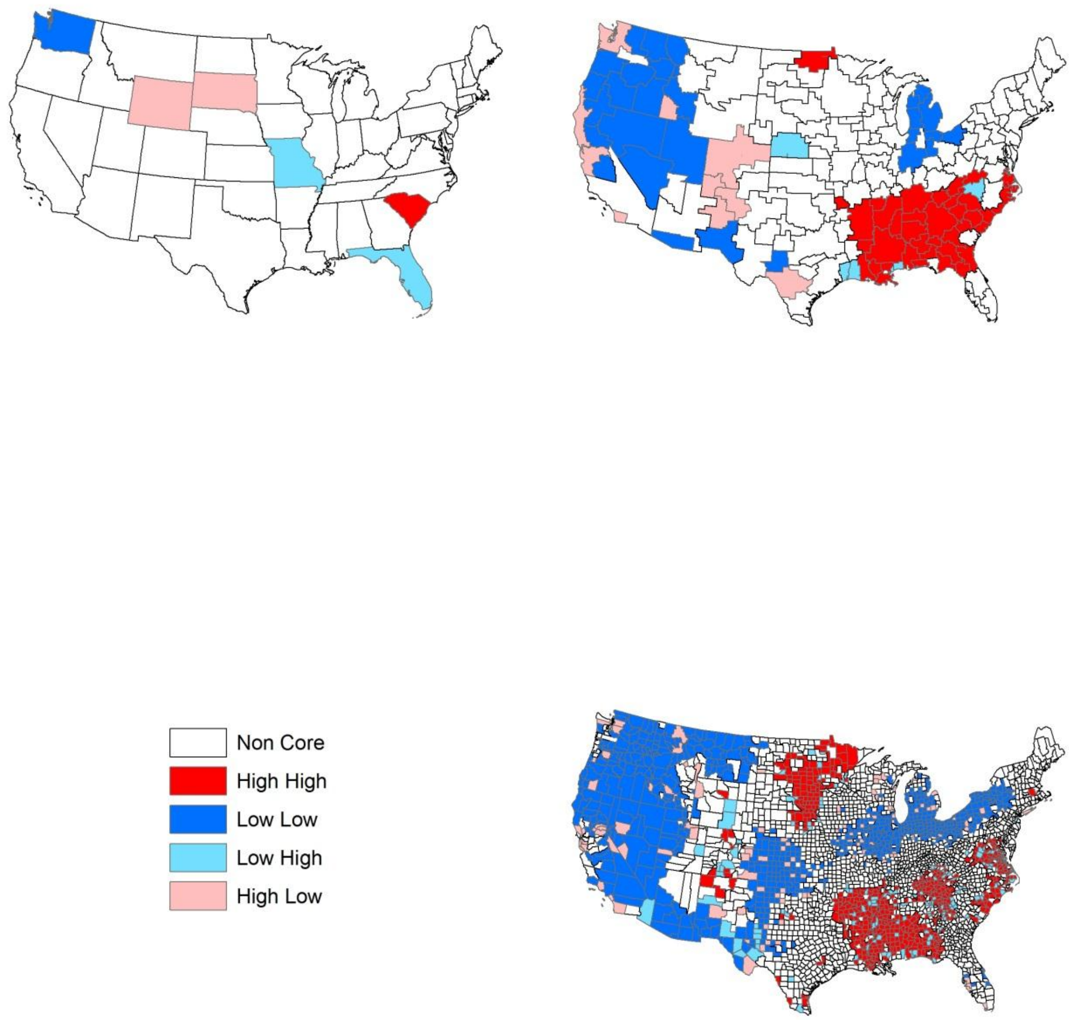

Figure 14: PCPI Change Second Order LISA Clusters

out west is much smaller at this scale. It is centered on Washington, and thus includes Montana, California, and Nevada, the latter of whom form the core of the hot spot. The EA and county cluster maps are consistent with this cold spot. Included in this cold-cold cluster at the smaller scale is Oregon, which is a part of a cold spot at the state level due to one second order neighbor (Wyoming) being classified as a high-low outlier. In the smaller scale maps, a consistency with the first order analysis is the classification of urban areas as a high low spatial outliers. This provides further evidence to the role of urban areas in growth, as well as provides evidence of the concentration of growth in cities in that region. In other words they appear to have served as economically primate cities in the region.

As a whole, the second order analysis offers some useful information regarding the nature of convergence as well as for the construction of the confirmatory model. The first aspect is the apparent inappropriateness of the second order weight matrix. For states, the global Moran's I is relatively weak and LISA clusters are relatively sparse. This indicates that second order neighbors are at the outmost edge of spatial dependence at the state level. Second order neighborhoods also are comparatively weak at the lower levels of aggregation, though still significant and with LISA clusters in the expected location. In addition the location of the LISA clusters offer confirmation of the presence of regional convergence clusters in the Southeast, west, and Rust Belt at the smaller scales. This provides further evidence of the convergence of incomes in the study period, indicating the appropriateness of it as a study period for the confirmatory models. Also, urban areas continue to be important as growth centers in the southeast, and as spatial outliers in places of slower growth. This suggests the urban variables in the confirmatory models will be important.

Conclusion

This chapter used ESDA techniques on 1970 PCPI and PCPI change 1970-2004, the dependent and main predictor variables in later confirmatory models. The goal of this chapter was to analyze the underlying spatial structure in the convergence process, identify an appropriate spatial weight matrix, and identify the initial regions expected to converge, all while comparing results across scales. In the identification of the spatial structure of the dependent and main predictor variables, first order and second order analyses produced similar results. Both variables exhibit positive spatial autocorrelation at statistically significant levels. Positive spatial autocorrelation indicates there to be the strong regionalization effect to be in place in the convergence process. In addition, the presence of spatial autocorrelation provides the first bit of statistical evidence that the traditional OLS approach to convergence testing is not appropriate. With spatial autocorrelation of the dependent variable (PCPI change), observations in the regression are not independent of each other, thus violating an assumption of regression analysis. A spatial model will solve that violation. Also, when the first order and second order analyses are compared, the degree of spatial autocorrelation is greater with the first order neighbors. This not only reinforces Tobler's Law, but also suggests that a first order neighborhood to be the appropriate definition for the spatial models, since it will correct for the greatest degree of spatial autocorrelation.

In addition to reinforcing the idea that convergence is a spatial process, the ESDA results also offered additional justification to the variables selected to include in the multivariate model of Chapter 7. At the core of this justification is the consistent outlier status of urban areas in the converging regions. In the Southeast, the largest urban centers were high-low outliers in the initial condition cluster maps, and continued to grow quickly over the study period. This indicates that urban areas may serve as growth centers in a converging region. On the other hand, in the places of initial wealth, urban areas tended to be places more immune to the slowdown, especially if they were centers of knowledge and skilled activity, such as the Bo-Wash region and San Francisco. Applied to the multivariate model, this would reinforce the need to include not only measures of urbanity, but also employment specialization, to account for the growth associated in the growth center urban areas in the bottom up converging region, but also in the immunity of urban areas with skilled labor forces in the regions of initial wealth.

Finally, the ESDA also offers insight in to M.A.U.P. issues associated with convergence model. A first aspect is related to the discussion of spatial weight matrices above. Although a first order matrix appears to be the most appropriate definition, a second order matrix is still serviceable at lower levels of aggregation. In other words, if there is a slight model misspecification through the use of too large a neighborhood, the smaller scales will be more robust against the mistake than the larger level of aggregation. In addition, the strength of spatial autocorrelation varied by scale, and not in the expected M.A.U.P. direction. Instead of the largest levels of aggregation offering the highest degree of association, the highest degree of spatial autocorrelation tended to be with the functional Economic Areas, which is a result to be further explored in the confirmatory models.

CHAPTER 6: BIVARIATE UNCONDITIONAL CONVERGENCE MODEL

Purpose and Organization of Chapter

In the previous chapter, the initial statistical evidence began to show the impacts of spatial and scalar effects in convergence modeling. The dependent variable, PCPI change, was shown to exhibit positive spatial autocorrelation regardless of the level of aggregation. In conjunction with the strong spatial autocorrelation displayed by the dependent variable, the main predictor, 1970 PCPI also displayed a strong degree of positive spatial autocorrelation across scales. This level of spatial autocorrelation violates the assumption of independence of observations for regression models. Thus, the results of the last chapter indicate the need for a spatial modeling approach, as well as provide the first hint of evidence as to a reason why convergence studies are contradictory. Failure to account for independence among observations can lead to inflated p-values, which can show significance that might not be present.

The effects of aggregation size on model results also began to surface as spatial dependence varied by aggregation unit. State level aggregation tended to have the weakest level of dependence, which is contrary to what would be expected from the M.A.U.P. literature. The strongest dependence tended to be at the functionally independent EA level. Even the nature of the spatial dependence can vary by the level of aggregation size, thus creating another reason for model disagreement and the inappropriate approach of the across the board model typically used in convergence studies.

The goal of this chapter is to build upon the results of the previous chapter through an analysis of the traditional Baumol-style beta convergence test. In this chapter, the Baumol-style bivariate regression is applied to states, EAs, and counties to test for beta convergence and identify the impacts spatial and scalar effects can have on model results. To do so, the chapter is divided in to three sections: OLS, first order spatial models, and second order spatial models. In the OLS section, the Baumol-style OLS regression is applied to the three scales, where PCPI change is used as the dependent variable against 1970 PCPI. This model will serve as the baseline test for the convergence evidence to be compared across scales. In addition, it provides the test cases in which LM multipliers can be applied to determine whether the spatial lag or spatial error modeling approach is most appropriate. Model residuals are also tested through a LISA analysis to detect regional under- or over-performance of the model which can offer insight as to additional predictors that can be added.

The second section of this chapter uses the same set up as the Baumol-style OLS, but includes first order spatial effects. Here, a spatial lag or error model is chosen according to Lagrange Multiplier (LM) results from the OLS diagnostics. Beta convergence results are compared both across scales to detect differences in results based upon aggregation unit. Spatial model results are also compared to OLS results at the same scales in order to determine if the spatial component improves model fit, diagnostic performance, and impact that the inclusion of spatial effects have on the convergence evidence. Similar to the OLS model, a LISA cluster analysis is applied to residuals in order to identify regional clusters of over- or under-performance. In addition, the LISA clusters can be compared to the OLS results in order to determine the improvement of the spatial model in accounting for spatial dependence.

The final section of this chapter is the second order spatial model analysis. Here, the same lag and error models are run, but with a second order neighborhood definition. Results are again compared across scales and to the OLS and first order counterparts. Models are compared through model fit and traditional diagnostics. LISA cluster maps of residuals are also run for the same purposes and to compare across scales.

Ordinary Least Squares

In order to provide consistency across models, any data transformations that are needed for the conditional models in Chapter 7 to pass diagnostic analysis are applied here as well. The dependent variables need no transformations at any scale. However, for the independent variables, a square root transformation is applied to states and counties, and a natural log transformation is applied EAs. The final models are as follows (Equation 15 for states and counties and Equation 16 for EAs):

$$C_i = k + \beta * SqrtPCPI_i^{1970} + \epsilon \tag{15}$$

$$C_i = k + \beta * lnPCPI_i^{1970} + \epsilon \tag{16}$$

Where:

C_i is 1970-2004 PCPI change in area *i*

$PCPI_i^{1970}$ is 1970 PCPI in area *i*

The results of the Baumol-style OLS models are displayed in Table 14, and immediately a few things are apparent. First, there is a large disparity in goodness of fit across scales, with the better fit coming as level of aggregation increases. This is not unexpected, as Gehlke and Beihl (1934) found that correlation coefficients increase as aggregation increases and the bivariate model is a very similar procedure. In terms of scalar comparison, the state level aggregation provided the largest log likelihood of -198.032, with the EA level decreasing to -720.98, and the county level regression performing comparatively poorly with a log-likelihood of -14588.5. While this type of relationship is expected, the drastic decreases in log-likelihood values as aggregation decreases points to an interesting aspect of the data. A possible reason behind increases in model fit and correlation as aggregation increase is that variation across individual

Table 14: Bivariate OLS Results

Scale	States	Economic Areas	Counties
Log-Likelihood	-198.032	-720.98	-14588.5
AIC	400.064	1445.96	29180.9
Schwartz	403.848	1452.31	29193
Beta Coefficient (P)	- 0.99 (0.02)	-56.67 (0.00)	-2.03 (0.00)
Constant (P)	239.30 (0.00)	636.80 (0.00)	291.93 (0.00)
Jarque-Bera (P)	2.6 (0.27)	1.15 (0.56)	262658.4 (0.00)
Breusch Pagan (P)	7.60 (0.006)	0.74 (0.39)	29.98 (0.00)
LMErr (P)	16.60 (0.00)	24.70 (0.00)	575.92 (0.00)
LMLag (P)	17.30 (0.00)	40.50 (0.00)	378.09 (0.00)
Robust LMErr (P)	0.038 (0.846)	2.33 (0.13)	198.03 (0.00)
Robust LMLag (P)	0.733 (0.392)	24.69 (0.00)	0.19 (0.66)

Note: 1970 PCPI received a square root transformation, while EAs received a natural log transformation

observations gets masked, making values at larger aggregations move closer towards the mean. Model fit decreasing at the smaller scales implies a greater degree of variation among individual observations. So, while testing for convergence at a large level of aggregation may produce better results in terms of model fit, the model also provides less insight as it simply masks data variation.

In terms of convergence evidence, distinct pattern emerges, although in the opposite direction. Here, the smaller levels of aggregation provide the strongest evidence of beta convergence, with p-values for 1970 PCPI significant at the 0.01 level. Conversely, the p-value for 1970 PCPI at the state level is only significant at the 0.05 level. This is consistent with masking of data variation at larger levels of data aggregation. As level of aggregation increases, the range of 1970 PCPI values decreases, from $25,113 at the county level to $2,443 at the state level, with standard deviations of $964.82 and $607.17, respectively. With less variation, there should be less of a "correction" to come from the regression coefficients. So, when testing for beta convergence, it appears that stronger evidence can come from smaller levels of data aggregation simply as a function of the underlying data.

While these models already show the effect of aggregation level on model fit and beta convergence evidence, it is in the residual diagnostics where the differences between these models becomes more apparent. Breusch-Pagan and Jarque-Bera tests are run to test for heteroskedasticity and normality, respectively. Only the Economic Area regression passes the traditional diagnostics. The state level regression passes the Jacque-Bera test for normal residuals, but fails the Breusch-Pagan test for heteroskedasticity. The failure of the Breusch-Pagan test is a bit more disturbing than the normality check, as it indicates some additional force influencing the processes is omitted from the regression. For counties, the OLS model fails both diagnostics, indicating the possibility of omitted variables and that a linear model may not be the best approach for this large data set. So, from the traditional OLS perspective there is already a clear difference in model performance across scales.

When spatial diagnostics are applied, each model faces additional problems. The Lagrange Multiplier results indicate the no OLS model is free of first order residual spatial autocorrelation. For the state model first order residuals, the LM results are significant for the lag and error models, and the Robust LM came back as insignificant for both. This indicates a larger specification problem for the model, which adds further evidence to a main point of this dissertation-- that using the same model across scales is a flawed approach. A possible solution to the specification issue is to add additional predictor variables. For the spatial model selection, since the spatial lag Robust LM is closest to significance, the spatial lag model is selected for states. The LM for EAs is significant for both models, but only the lag was significant in the Robust test and is so selected. Counties also display a significant LM, but with the error model emerging as most significant. Of interest here is the fact that different spatial models need to be used on the different scales. For Economic Areas, the use of the lag model points to agglomeration effects spilling over outside of functional economic areas. For counties, the error model suggests that there is a large correlated regional effect at work. This means that counties could be capturing larger regional processes, and the value in a county cannot be simply explained by and caused by the value in a neighbor.

Figure 15 shows the LISA clusters for state, EA, and county OLS residuals. Fitting with the high degree of spatial dependence, all of the cluster maps show a large presence of hot and cold spot activity. For states, there are large cold spots in the western United States, as well as in the Rust Belt. This is not entirely surprising since the Rust Belt was the area of the United States to experience the greatest impacts of deindustrialization during this time period, and the western United States is characterized

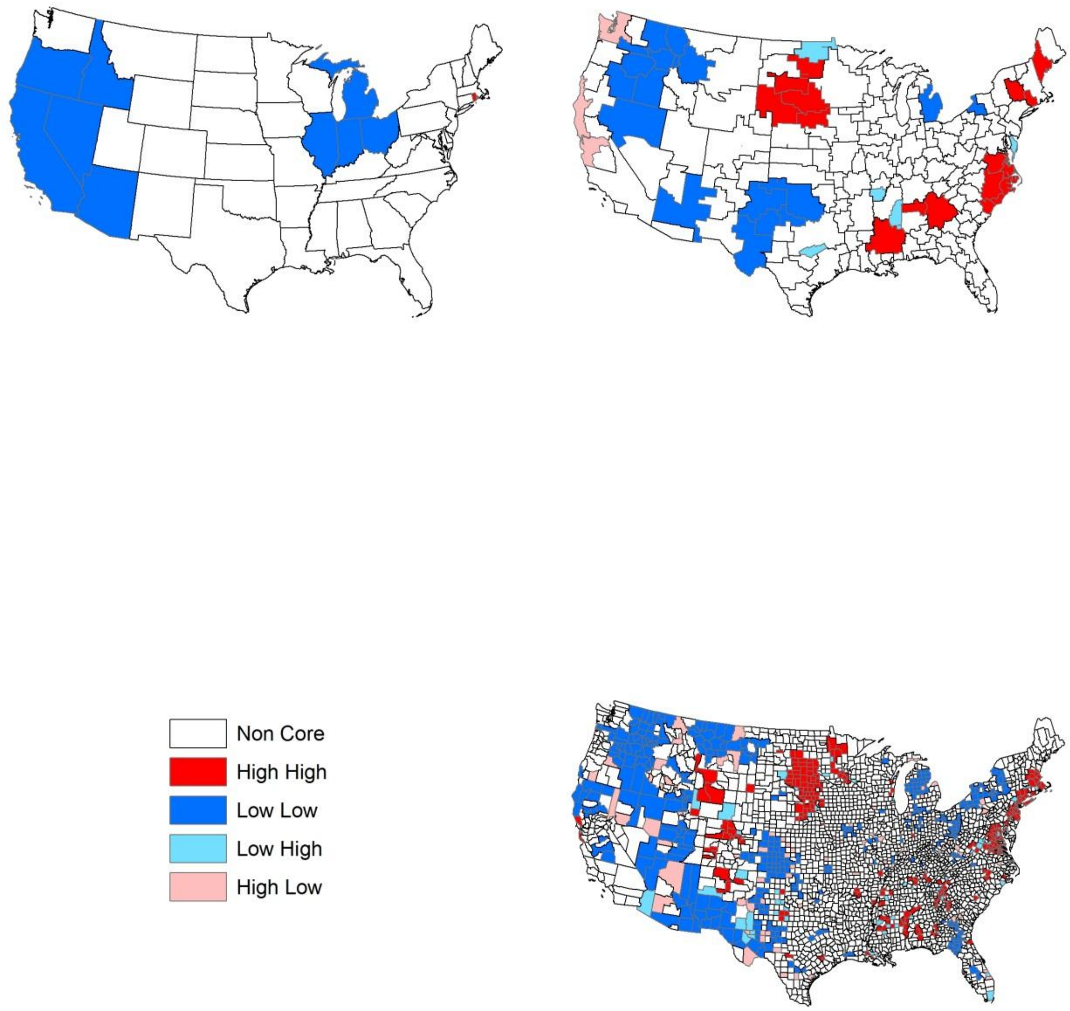

Figure 15: Bivariate OLS Residual LISA Clusters

by a few cities of relative wealth, surrounded by large counties with a more primary sector focused economy. Further insight can be gained by looking at the EA and county cluster maps. For Economic Areas, the hot spots in the east are centered on large cities that experienced a rapid growth of the technologies of the latest Kondratieff such as New York, Boston, and Raleigh. Additionally, in the Southeast, the regional command centers of Atlanta and Birmingham are again hot spots of activity, suggesting their importance in the regional growth of the south. There is an additional cold spot centered on Detroit, and another in western New York. This would suggest that the urban areas that focused heavily on Fourth Kondratieff Fordist manufacturing performed exceedingly poorly, while places that were able to become important in the new driving sectors not only performed quite well, but also were able to have a positive impact on regional growth. On the west coast, the disparity between the urban areas and their neighbors becomes more clear as San Francisco and Seattle served as hot spot cores of spatial outliers, being surrounded by cold spots. This indicates that these urban areas performed quite well, although little spill over to neighbors occurred. This is in contrast to the urban effects seen on the east coast, and may be attributed to the larger county sizes in the western United States, where that any spillover effects would have a larger area in which to spill over to have as strong of a regional effect. The county maps paint a similar picture to the EA maps. Along the east coast, the counties in the Bo-Wash area show up as hot spots, further indicating the concentration of growth within urban areas that were centers of the new economy. Counties in western New York and other Rust Belt counties again returned as cold spots, reflecting their poor performance in the deindustrialization era. Out west, large portions of the region show up as cold spots, with a few urban areas serving as spatial outlier hot spots, further reflecting the concentration of growth within urban areas and the lack of spill-over to the more rural and larger counties.

Drawing the results of the spatial diagnostics together, the importance of spatial effects in the convergence process becomes quite clear. First, the LM results indicate a lack of independence in the residuals, which indicates that a spatial model is more appropriate approach than OLS. Second, the EA and county models suggest the presence of agglomeration effects for urban areas, an effect that can be captured through a spatial model. In addition, the OLS models display strong regionalization in residuals. As a whole, the OLS model did a reasonable job in accounting for the growth in the bottom up converging Southeast. Outside of a few urban areas, notably Atlanta and Birmingham, the Southeast was mostly a non-core region. However, Rust Belt areas are dominated by a cold spot, indicating the models underperformed when it came to predicting the deindustrialization in the region. In particular, the models underperform in the areas strongly associated with Fordist manufacturing. In this case, the cold spot indicates that the beta coefficient was not strong enough to show the weakness in growth rate. In other words, in the Rust Belt there are additional effects at work other than just initial levels of income. This is contrasted to the Bo-Wash and Southern results, where urban areas seemed to be a cause of rapid growth, enough to move outside of the expected in the models, whether it be fast growth in the south or slow growth in the north. Out west, this urban effect is shown in both categories, as the urban centers focusing on new technologies ended up as high low outliers, and the more rural hinterland areas ended up in low-low clusters. While these also showed up as spatial clusters, indicating the need for a spatial model, they also brought evidence that additional variables such as industrial specialization and urbanization may need to be included in the model.

First Order Spatial Models

In these models, the results from the LM tests applied to the OLS models in the previous section are used to construct a spatial model at each scale. The data transformations in the OLS model are applied here as well. Lagrange Multiplier results indicate that state and EA models are best specified with a spatial lag, and the county model through a spatial error. This gives the following specifications (Equations 17 for states, Equation 18 for EAs, and Equation 19 for counties):

$$C_i = k + \beta * SqrtPCPI_i^{1970} + \beta W\lambda + \epsilon \tag{17}$$

$$C_i = k + \beta * lnPCPI_i^{1970} + \beta W\lambda + \epsilon \tag{18}$$

$$C_i = k + \beta * SqrtPCPI_i^{1970} + \beta W\varepsilon + \mu \tag{19}$$

Where:

C_i is PCPI change in area *i 1970-2004*

$PCPI_i^{1970}$ is PCPI in area *i* in 1970

W is the spatial weight matrix

λ is the spatial lag of C_i defined by weight matrix W

ε is the vector of spatially autocorrelated error terms defined by weight matrix W

μ is the vector of errors

Table 15 displays the results of the spatial models. The log-likelihood values for each model improve versus their OLS counterparts, reflecting a better model fit when spatial effects are taken into account. In addition, the AIC and Schwartz tests are also smaller than the OLS counterparts reinforcing the better fit of the spatial models. Comparing the spatial models to each other, their model fit is in a similar pattern to the

OLS models, where model fit decreases whens aggregation level increases. The smallest log-likelihood, AIC, and Schwartz values are at the state level, and the largest at the county level. The difference between states and counties is dramatic: the log-likelihood for states is -189.79, EAs is -703.01, and counties is -14387.02 also suggestive of the

Table 15: Bivariate First Order Spatial Model Results

Scale	States	Economic Areas	Counties
Log-Likelihood	-189.79	-703.01	-14387.02
AIC	385.57	1412.02	28760
Schwartz	391.25	1421.55	28722.1
Beta Coefficient (P)	-0.48 (0.15)	-34.17 (0.00)	-1.93 (0.00)
Constant (P)	95.99 (0.00)	366.30 (0.00)	286.61 (0.00)
Breusch Pagan (P)	7.70 (0.01)	1.28 (0.26)	6.69 (0.01)
Spatial Variable (P)	0.63 (0.00)	0.50 (0.00)	0.48 (0.00)

great degree of data masking occurring at the larger level of aggregation. Only the Economic Area model passed the Breusch-Pagan test, indicating that both states and counties failed to capture certain effects that caused the models to again produce heteroskedastic residuals. For states, this is not surprising, given the poor model specification indication by the Lagrange Multiplier tests. For counties, this is also not entirely surprising given the relatively small level of aggregation. Of note, however, is that the addition of the spatial variable reduced the Brush-Pagan values in all models versus their OLS counterparts indicating that space is a factor in causing hetereoskedastic residuals, though for states and counties, it does not appear to be the only one.

The evidence for beta convergence in the spatial models is similar in nature to the evidence in the OLS model; it strengthens as aggregation size decreases. For states, the beta coefficient is negative, but the p-value of 0.15 indicates it not to be a significant predictor. Economic Areas and counties both have coefficients for 1970 PCPI that are significant at the 0.01 level. What is worth noting about the beta convergence evidence is that the beta coefficients are smaller at each level versus the OLS models. This indicates that while the addition of the spatial component improved model fit, it actually took away some of the importance of 1970 PCPI. With the increase in model fit, as well as decrease in strength of the beta for 1970 PCPI, the spatial component should be significant, as is the case in all models. For states, the coefficient is 0.63, EAs at 0.50, and counties is 0.48. What is interesting about the state model is that since the other predictor was not significant, the model is essentially an interpolation procedure. The significance of the spatial variable in the other models is at the highest level, and the coefficients are of roughly the same value. However, the difference in the model type is where it becomes interesting. In the lag EA model, the value of the spatial component indicates that the value of PCPI change in an observation is positively and directly related to the change values in its neighbors. However, in the county error model, the value of the PCPI change in an observation is positively related to the values of its neighbors, though it cannot be assigned to be a causal relationship. Thus, while the strength of the spatial aspects in these two models is similar, the underlying reasons behind the spatial dependence are slightly different.

In Figure 16, the LISA cluster maps are displayed. There are comparatively fewer clusters at the state level than in its OLS counterpart, and the clusters remaining are smaller in size. There is still a cold spot in the western United States, but the cold spot is much more concentrated. New York serves as a cold spot spatial outlier in the Northeast, and New York appears to be subject to the influence of the decline of its western

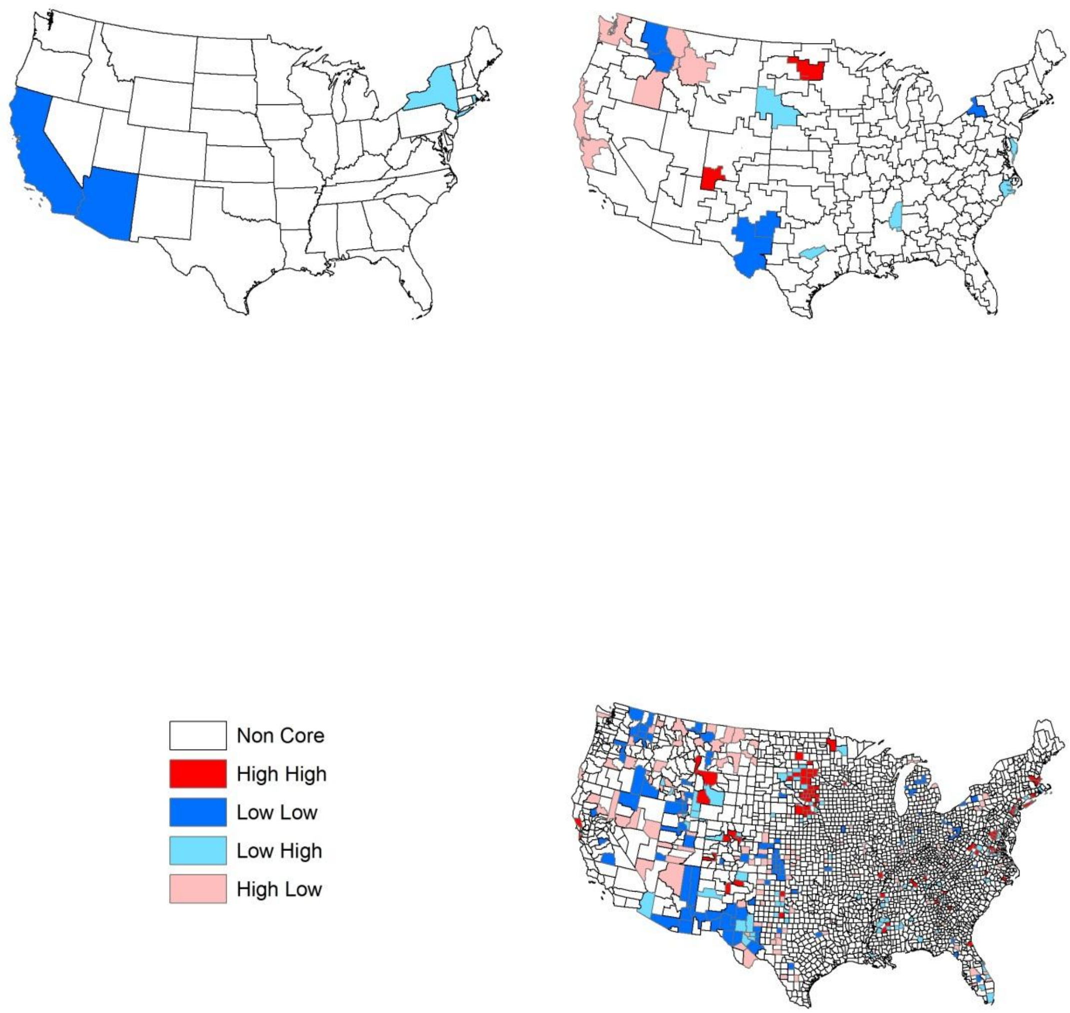

Figure 16: Bivariate First Order Spatial Model Residual LISA Clusters

manufacturing region, while New England has experienced growth. In the EA map, the LISA clusters are again fewer in number than in the OLS model. However, with the presence of the high-low spatial outliers in the west coast, there still is the possibility of agglomeration effects occurring in those urban areas that are not spilling over to their neighbors. Or, perhaps more disturbingly, the urban area may be serving as a failing Growth Pole that is drawing potential investment in the hinterland to the urban core and creating a backwash effect. With counties, there is a distinct pattern of randomness in the errors from the Mississippi River westward. This would suggest that there is something additional causing a great disparity in the residuals, but it is highly localized. There are still patterns of hot spot activity on the east coast and San Francisco. The hot spots on the east coast are constrained largely to the areas around Boston, New York, and Washington, which in conjunction with the presence of San Francisco indicates that there are still some urban areas with a focus in the new economy that simply outperformed the rest of the county.

The results of these models provide a few interesting insights as to how space and scale can affect convergence test results. At larger scales, the models are the strongest in explanatory power but weakest in evidence for beta convergence. This is not entirely surprising, since large units of aggregation remove much of the variation needed for an informative regression model. The solution, however, is not to simply use the smallest level of aggregation possible, as the county results had problems with the residuals in both the OLS and spatial models. This may be related to the nature of counties; they are politically defined units, not functional units like EAs. As such, their economies can be expected to be driven by some of the same economic forces as the other members of the

EAs or MSA. While the expectation may be that the spatial model would account for that, the counties at the edge of the functional EAs have neighbors in two EAs, thus including the processes from two functional economies. As such, the spatial model would still only be accounting for partial influence in those edge counties, including the weights coming from different functional economies. Thus, the small size of the counties and their non-functional nature may lead to residual errors, as noted in both the spatial and non-spatial models. A possible way to address those residual errors would be to include additional variables in the convergence test, thus extending it past the traditional Baumol-style model. The results for EA regressions are the most promising. Without thinking about space, the regression fared quite well in the OLS approach. But once the residuals were tested, there was a degree of spatial dependence even within these functional economic units. Once the spatial lag term was included, all of the residual analyses became acceptable and model explanatory power increased. This points to a key finding of this dissertation: the results of beta convergence tests are highly sensitive to the level of spatial aggregation. In applying this simple model to a functional (not political) unit, the regression performed quite well in model fit, diagnostics, and hypothesis tests. Thus, in future work regarding the convergence debate, spatial aggregation should be taken in to account and data should be aggregated to the economically functional scale. In addition to scale selection, there is another key finding from this analysis: that different spatial scales are subject to different spatial effects. The state and EA models performed best with a spatial lag, while counties performed best with a spatial error model. So, in testing for beta convergence, while the test is standardized in terms of variable selection, model choice is still something that needs to be approached with care and with careful understanding of the study area.

Second Order Spatial Models

In the OLS and first order analyses, spatial effects are shown to be quite prominent, as the inclusion of the spatial component improves both model fit and model diagnostics. In this section, the neighborhood matrix is expanded to second order neighbors, and the regression models are run again. Results are again compared across scales and to the previous OLS and spatial models.

Table 16: Bivariate Second Order Lagrange Multipliers

Scale	States	Economic Areas	Counties
LMErr (P)	0.51 (0.48)	13.36 (0.00)	577.33 (0.00)
LMLag (P)	0.31 (0.58)	24.60 (0.00)	338.1 (0.00)
Robust LMErr (P)	0.37 (0.53)	0.41 (0.52)	242.35 (0.00)
Robust LMLag (P)	0.18 (0.67)	11.66 (0.00)	3.12 (0.08)

The first step in this second order analysis is to run the OLS models again, but this time use the new weight matrix in in the LM tests. The only thing to change in these models from the OLS results are LM results, so only LM results are displayed in Table 16. Immediately, a few interesting results are noticeable. First there is the complete lack of significance at the state level. This indicates that when neighbors are extended out to a larger region, the similarity across states ceases to be statistically significant. For model calibration, this means that the second order weight matrix will fail to account for the spatial autocorrelation known to be present. At the EA level, the relationship is also not as strong as in the first order analysis, as the values simply are lesser in size indicating a weaker relationship, even though still statistically significant. At the county level, the results are somewhat surprising. The spatial dependence is actually greater than at the first order. This is in contrast to the relationships at the larger levels of aggregation, as well as the significance of county level variables in the ESDA chapter. This surprising results is one that needs to be further explored through residual and model diagnostics.

The spatial model results are displayed in Table 17. No model is run at the state level due to the insignificant LM results. At EA and county levels, diagnostics for model fit indicate the second order model performed slightly worse than the first order

Table 17: Bivariate Second Order Spatial Model Results

Scale	States	Economic Areas	Counties
Log-Likelihood		-711.24	-14416.29
AIC		1428.49	28836.6
Schwartz		1438.01	28848.65
Beta Coefficient (P)		-42.02 (0.00)	-1.76 (0.00)
Constant (P)		434 (54) (0.00)	277.34 (0.00)
Breusch Pagan (P)		0.63 (0.43)	10.00 (0.00)
Spatial Variable (P)		0.47 (0.00)	00.57 (0.00)

model. Log-likelihood values for EAs increased from -703.01 to -711.24; for counties they increased from -14387.02 to -14416.29. AIC and Schwartz values increased at both scales as well. These increases are marginal, but begin to suggest that the second order model is not as appropriate as the first order model. In addition, the results are consistent with all other regression results where the larger level of aggregation produces better model fit, as the EA has a comparatively smaller log-likelihood values than the county model. Evidence for beta convergence is present in both models, and significant at the 0.01 level. The coefficient for EAs is more negative than in the first order model, which indicates the additional variation needed to be captured through the 1970 PCPI, which did not do as good of a job as the spatial lag, reflected by the worse model fit. In contrast, the beta for 1970 PCPI in the county model is slightly larger (closer to 0) than in the first order model. That indicates that the spatial variable is able to account for more of the dependent variable. However, with the decreases in mode fit, it appears that the additional strength of the spatial variable comes at a price, implying that the first order model may still be a better approach, or that additional variables need to be added.

Residual LISA maps are displayed in Figure 17. Again, since no model for states is run, the state map contains no variables mapped. At the EA level, there are relatively few clusters, again showing the ability of the spatial model to account for spatial dependence. However, with the weakening of the spatial relationships reflected by the second order LM tests, the presence of comparatively few clusters is understandable. It is not that the second order matrix does a better job of capturing spatial effects. Rather, EAs may be large enough where it is difficult to create a critical mass of observations to capture a true regional effect. In fact, only 17 EAs serve as cores, meaning that less than 10 percent of EAs fall in to that category. A hot spot is still present in the Bo-Wash region, again suggesting an inability of the bivariate model to fully account for urban agglomerations that have a specialization in high knowledge industries. A Rust Belt cold spot is also present, starting in upstate New York, and continuing through the Great Lakes region. The cold spot is pronounced with low-low clusters in upstate New York, and is much more defined with high-low outliers in conjunction with a few low-low clusters. This indicates that there are a large number of counties in the Rust Belt where the model over predicted income change. With the existing negative beta, this again means that the

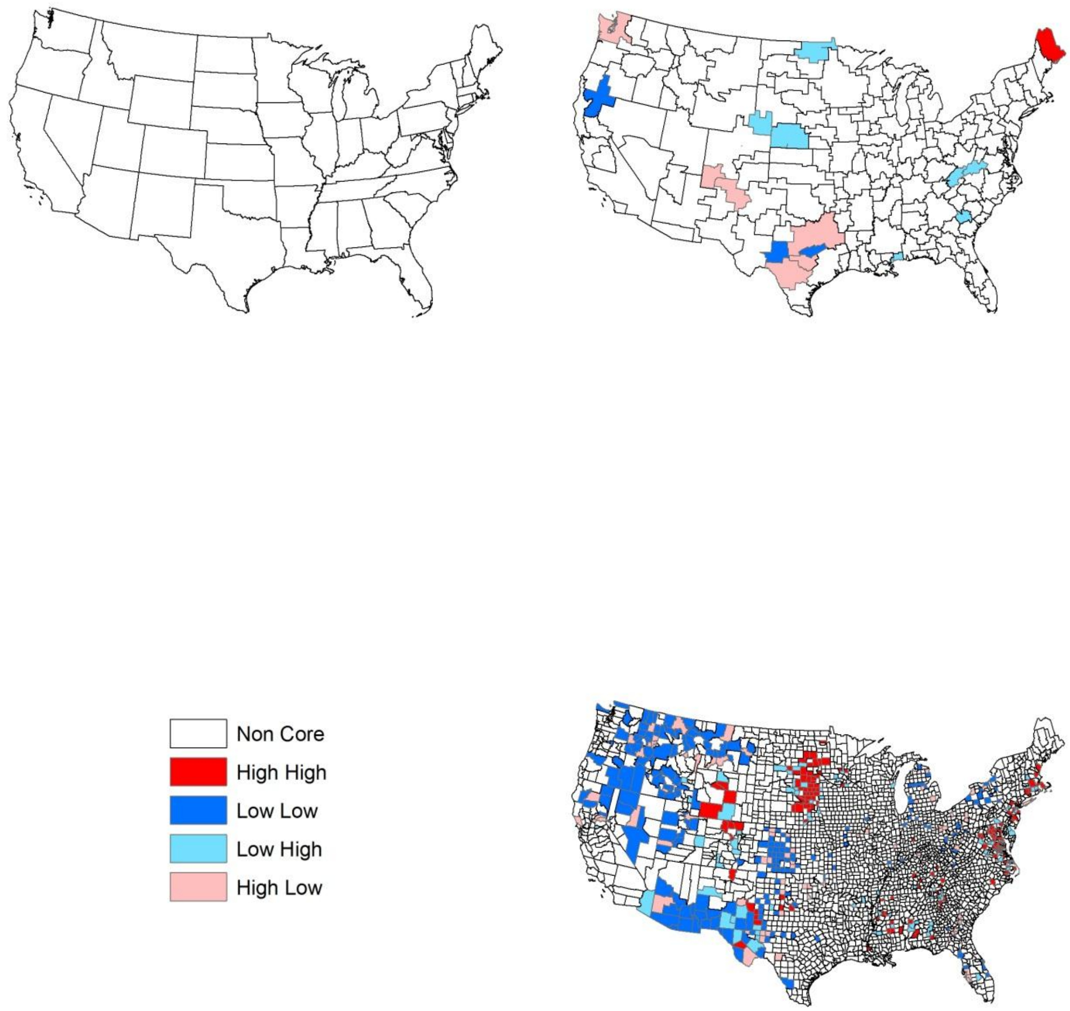

Figure 17: Bivariate Second Order Spatial Model Residuals LISA Clusters

PCPI model did not capture the magnitude of deindustrialization in the Rust Belt. The spatial outliers are generally in urban areas, but in urban areas such as Columbus, OH that were late arrivers in the industrial region, or suburban counties such as Oakland County, MI, who were able to capture regional industrial relocation in a decaying region, or an old urban core, such as Summit County Ohio, which was able to invest in a new knowledge industry. But, these few outliers indicate that their success was unique to themselves.

Out west, the cold spot in the first order residuals persists in the second order residuals. The location of the cold spot mirrors the first order as well; it does not extend in to the coastal regions, but traces through California, Nevada, Oregon, Washington, and Idaho. With the placement of these counties of this interior region, the urban-rural effect evidence continues to persist as these rural components of the former western hot spot grew even more slowly than their PCPI should have called for, in contrast to the urban, tech centered economies on the west coast. This rural aspect persists in the cold spot stretching through Arizona and Texas, also home to a hot spot in initial PCPI.

In this section, spatial models are run using a second order neighborhood matrix for model calibration. In these results, several findings from the first order and OLS models are confirmed, as well as new insight gained. Of particular interest to this dissertation is the reinforcement of the importance of spatial and scalar effects in interpreting convergence evidence and model construction. The most striking evidence of this is at the state level where, due to the size of states, the second order neighborhood is useless in capturing spatial effects and dependence. Even at the smaller scales, the second order model produced slightly different results of convergence evidence, where the spatial variables capture different levels of variation, and thus create different coefficients for 1970 PCPI. In this case, the convergence evidence is strong enough where p-values remained significant, the evidence is here that a differing model calibration could move evidence to significant or insignificant if model calibration is borderline. However, there were some consistencies with the first order and OLS models. First, there was uniform evidence of convergence in the models. Second, the models tended to under-predict in the same areas; there were prediction problems in the Rust Belt, west coast, east coast, and in extreme urban/rural areas. This reinforces that spatial effects may not be enough to capture everything in a convergence model.

Conclusion

In this chapter, the traditional, bivariate, Baumol-style convergence test were run at the state, EA, and county level of aggregation using OLS, first order, and second order spatial models. The results of each model were analyzed for convergence evidence, model fit, and both spatial and non-spatial diagnostics and compared across scales. The results provide evidence of convergence at all scales. In addition, results suggest a need for a spatial modeling approach, that scale plays an important role in model construction and results, and a need for a conditional model to more fully explain the convergence process at different scales.

One consistent aspect of all models, regardless of scale or specification, is the evidence for beta convergence. In the OLS and spatial models, the betas for 1970 PCPI are negative, consistent with the Baumol expectations. However, the strength of the relationship is not uniform across scales. The smaller scales have more significant p-values than the state models. In fact, when a spatial component is included, the significant of PCPI at the state level goes away. These results indicate that even the simplest model is very sensitive to specification and M.A.U.P. issues providing evidence for inconsistency in the convergence literature. Depending on both the aggregation size and specification, it is entirely possible to have conflicting results using the same study area. Based upon these results, it is possible to find evidence, both confirming and rejecting convergence, in the United States 1970-2004, depending on aggregation size and if spatial effects are included. In general, however, the more detailed models provide evidence for beta convergence, so it is mostly likely to be present in the study period.

In terms of model performance, scalar and spatial effects were quite prominent. Regardless of scale, OLS models have difficulty in passing even the traditional diagnostics, as the EA model is the only to pass those. The EA model typically fares the best in traditional diagnostics, and it can be inferred that their functional nature provides a leg up on the political levels of aggregation in fully capturing smaller scale economic process. County level models have difficulty in passing the tests related to normality and constant residual variance, which could be due to the great degree of variation in the data and the myriad of underlying process that can drive economic growth at a county level. When spatial diagnostics are applied, OLS performance becomes quite suspect; as no model passed the first order LM tests and the smaller scales still failed the second order LM tests. In the bivariate spatial models, model fit and diagnostic performance improves across all scales, thus indicating the superiority of the spatial modeling approach. However, the spatial variables were not able to remove all residual diagnostic issues at the state and county level. The typical response to this type of problem is to include additional variables. This would indicate that even though accounting for spatial effects can greatly improve model performance, the simple bivariate model may not be the best approach for testing beta convergence at politically defined units.

LISA cluster maps provide insight as to variables to include a conditional model. While the model typically did very well in predicting regional growth in the Southeast, it performed relatively poorly in the Rust Belt and western regions. In the Rust Belt and east coast, the regional under-performance seems to be focused around urban effects and economic structure. Cities and urban areas serve as the centers of regional clusters, regardless of cluster type. In terms of type of cluster, the heavy manufacturing Rust Belt seemed to underperform, whereas areas with a greater degree of the higher knowledge sectors performed the best. Thus, the implication is that in order to account for this performance, some measure of urbanity should be included, as well as some measure of industrial structure. In the conditional model both of these aspects are included. Urban effects are accounted for through the inclusion of population and the urban-rural continuum value, and industrial structure is accounted for through the inclusion of Location Quotient in the FIRE and Service sectors. These industrial diversity measures are of particular interest, as the distribution of these in the standard deviation maps line up quite well with model residuals. In New England, there is a relative concentration of FIRE and service, whereas in the Rust Belt, both of these sectors fall relatively low in concentration. These factors should help account for some of regional underperformance and help improve model fit and diagnostic performance.

CHAPTER 7: MULTIVARIATE CONDITIONAL CONVERGENCE MODEL

Purpose and Organization of Chapter

In the previous chapter, a traditional Baumol-style unconditional convergence model was run at three scales using OLS and spatial models. Traditional OLS results all pointed to beta convergence, with a negative and significant coefficient for 1970 PCPI. However, even with such a simple test, M.A.U.P. and specification issues arose, with unequal convergence evidence, and with only one model (EA) passing the traditional diagnostics. The inclusion of the spatial component improved model fit in all cases, however heteroskedastic residuals remained problematic for the state and county level models. A traditional solution to this problem is to include more predictor variables in the model. When additional variables are introduced to an unconditional convergence model, it becomes a conditional model as the additional variables, if selected properly, control for the structure of the local economy. The diagnostic problems of the state and county level results suggest that a conditional approach may be more appropriate.

Additional support for the multivariate conditional model comes from the LISA cluster analysis of the bivariate residuals. The OLS residuals had a strong regionalization in the Rust Belt, Southeast, and west coast. In theory, the addition of the spatial variable should have controlled for spatial dependence in the residuals. Across the board LISA clusters, reflecting spatial dependence in the residuals, were smaller in scope and magnitude. However, the spatial model still had clusters in its residuals. Their pattern, however, points to the additional variables discussed in the literature review as theorized causes of convergence. As a whole, the model did a reasonable job in the prediction of the bottom-up convergence of the Southeast. Within the Southeast, urban command and control centers tended to grow faster than convergence theory would have suggested, indicating an importance of urbanity in the growth process. This is consistent with results from the Rust Belt and west coast clusters, where urban areas tended to be at the center of clusters. Urban areas at the center of cold spot clusters tended to be those that were solely focused on the old Fordist style of manufacturing or in primary activity, while outliers in regional cold spots tended to be urban areas focused on fifth Kondratieff production. This suggests that not only can urban effects influence the growth of a region, but the type of specialization can as well. Given that these areas were outliers in residuals, those are effects that should be controlled for in the model.

In this chapter, a multivariate conditional convergence model is applied to control for those effects, as well as investigate the impact additional predictors can have on convergence evidence, model fit, and diagnostic performance. To do so, multivariate models are run at the state, EA, and county level using OLS, first order spatial, and second order spatial models. As was the case in the bivariate analysis, the OLS model serves as the baseline for comparison. In the OLS section, convergence evidence and model performance are compared across scales and additional significant predictors are identified. Residual diagnostics are performed to test for model specification issues, and LM tests are used to test for spatial dependence and the type of spatial model needed to account for that dependence.

The second section builds upon the results for the OLS models. Here, the same multivariate models are run, but spatial effects are included in the manner indicated by the LM results. Model results are again compared across scales for convergence evidence, additional significant predictors, but also model fit, diagnostic performance, and the strength of the spatial effects as a predictor. LISA cluster analysis is applied to identify if the multivariate model accounted for regional underperformance in the bivariate model.

Similar to the previous experiments, this chapter concludes with a second order spatial effects modeling exercise. Here, the same lag or error models are run, but with a second order neighborhood weight matrix. Results are again compared across scales and to the OLS and first order counterparts. Models are compared through model fit and traditional diagnostics. LISA cluster maps of residuals are also run for the same purposes and to compare across scales.

Ordinary Least Squares

In order to improve model diagnostic performance, several data transformations are applied. The dependent variable remains untransformed at all scales, and the 1970 PCPI transformations from the bivariate model remain in place. The additional predictors are defined in Chapter 4. Below, Table 18 summarizes the variables.

At the state level, population, Rural-Urban Continuum, LQ Service, and LQ FIRE receive a square root transformation, while RTW and connectivity remain untransformed. In the EA model, natural log transformations are applied to LQ Service, LQ FIRE, population, and RTW average, while Rural-Urban Continuum and connectivity remain untransformed. At the county level, LQ FIRE, LQ Service is square root transformed, while the other variables remain untransformed. These transformations give us the final model specifications (Equation 20 for states, Equation 21 for EAs, and Equation 22 for counties):

Table 18: Variables

Variable	Variable Name	Source	Expected Sign
1970 PCPI	PCPI	BEA REIS	Negative
1970 Right to Work Status	RTW	National Right to Work Legal Defense Foundation	Positive
1970 Population	P	National Historic GIS	Positive
1974 Urban-Rural Continuum Code	R	United States Department of Agriculture	Positive
1970 Connectivity	C	Federal Highway Administration	Negative
1970 Service Location Quotient	LQS	BEA REIS	Positive
1970 FIRE Location Qoutient	LQFIRE	BEA REIS	Positive

$$C_i = k = \beta * SqrtPCPI_i^{1970} + \beta * RTW_i^{1970} + \beta * P_i^{1970} + \beta * SqrtR_i^{1974} + \beta * C_i^{1974} + \beta * SqrtLQS_i^{1970} + \beta * SqrtLQFIRE_i^{1970} + \epsilon \tag{20}$$

$$C_i = k = \beta * lnPCPI_i^{1970} + \beta * lnRTW_i^{1974} + \beta * lnP_i^{1970} + \beta * R_i^{1970} + \beta * C_i^{1974} + \beta * lnLQS_i^{1970} + \beta * lnLQFIRE_i^{1970} + \epsilon \tag{21}$$

$$C_i = k = \beta * SqrtPCPI_i^{1970} + \beta * RTW_i^{1970} + \beta * P_i^{1970} + \beta * R_i^{1974} + \beta * C_i^{1974} + \beta * SqrtLQS_i^{1970} + \beta * SqrtLQFIRE_i^{1970} + \epsilon \tag{22}$$

Where:

$PCPI_i^{1970}$ is 1970 PCPI in location *i*

RTW_i^{1970} is 1970 Right to Work status in location *i*

P_i^{1970} is 1970 population in location *i*

R_i^{1974} is 1974 USRA rurality score

C_i^{1970} is 1970 connectivity in location *i*

LQS_i^{1970} is the 1970 Location Quotient for Services in area i

$LQFIRE_i^{1970}$ is the 1970 Location Quotient for FIRE in area i

W is the spatial weight matrix

λ is the spatial lag term

ϵ is the spatially autocorrelated error term

The results of the OLS models are shown in Table 19. One result worth immediate note is the similarity of results to the bivariate Baumol-style models of the previous chapter. Here, model fit also decreases as the level of spatial aggregation decreases. States have the largest log-likelihood of -186.24, EAs follow with a log-likelihood of -692.38, and counties have a log-likelihood of -14509.9. As is the case with the bivariate model, this should be expected according to M.A.U.P. theory, due to the variation that can be lost as aggregation unit increases. Compared to the bivariate models, all of the log-likelihood values are closer to zero, indicating better model fit. However, the relative decreases are all somewhat marginal. This would suggest that none of the additional variables offer quite the explanatory power of 1970 PCPI. Further, the additional variables did not remove the significance of the constant in the equations, suggesting the possibility of additional factors at play.

In terms of convergence evidence, all three model show evidence of beta convergence at levels consistent with their Baumol-style counterpart. Convergence evidence is strongest at the smaller levels of aggregation, where 1970 PCPI is significant at the 0.01 level for counties and EAs, but only the 0.05 level for states. This result is consistent with the bivariate results, where smaller levels of aggregation provided

Table 19: Multivariate OLS Results

	State	Economic Area	County
Log-Likelihood	-186.24	-692.38	-14509.9
Jarque-Bera	6.26 (0.044)	0.54 (0.76)	385500.5 (0.00)
Breusch-Pagan	14.55 (0.042)	21.51 (0.003)	30.66 (0.00)
Constant (P)	229.68 (0.00)	974.34 (0.00)	283.13 (0.00)
1970 PCPI (P)	-1.22 **(**0.03**)**	-77.06 **(**0.00**)**	-2.07 **(**0.00**)**
Population (P)	-0.001) **(**0.69**)**	0.009 (0.00)	0.0002 (0.30)
LQ Service (P)	18.41 (0.45)	6.00 (0.22)	8.79 (0.00)
LQ FIRE (P)	6.95 (0.79)	10.72 (0.015)	0.51 (0.46)
Right to Work (P)	6.45 (0.12)	0.96 (0.00)	9.43 (0.00)
Connectivity (P)	-0.16 **(**0.01**)**	-0.018 **(**0.43**)**	-0.03 **(**0.02**)**
Urban-Rural (P)	0.98 (0.098)	0.006 (0.66)	0.09 (0.00)
LM Lag (P)	10.81 (0.00)	17.68 (0.00)	275.52 (0.00)
Robust LM Lag (P)	10.95 (0.00)	6.94 (0.01)	0.89 (0.34)
LM Error (P)	(3.47 (0.06)	11.12 (0.00)	383.28 (0.00)
Robust LM Error (P)	3.61 (0.06)	0.39 (0.53)	108.65 (0.00)

the strongest convergence evidence. The implication of this result is actually the opposite of the expected M.A.U.P. result, where the increase in variation of the variables produces stronger relationships. Thus, the models not only indicate that initial levels of PCPI bear a very strong relationship with change, they also provide evidence that convergence processes may be best studied at smaller levels of aggregation. An interesting note lies with the coefficients and p-value of 1970 PCPI. The coefficients are actually smaller (more negative) with the inclusion of the additional variables, while the p-values are slightly weaker than in the bivariate model. This suggests that the addition of predictors required more correction to be needed from 1970 PCPI to lower the predicted values, since most of the predictors are positive in value. So, truth be told, it is not necessarily that the convergence evidence is stronger, as the p-values suggest otherwise, it may simply be that a larger coefficient was gained through 1970 PCPI serving as a control over the additional omitted variables.

The comparison of the additional variables is where the results become interesting. Although generally consistent across levels of aggregation in that urbanization, employment specialization, and connectivity are important, the actual strength of these effects varies by model. At the largest level of aggregation, the only two predictors to come back as significant are the Rural-Urban Continuum score and distance from population center to a major expressway. For the urbanization level, the beta coefficient is positive with a p-value of 0.098, significant at the 0.10 level. Thus, regions with a concentrated center of urbanized population grew at a faster rate than more rural areas. In other words, this fits well with urbanization (Jacobian) externalities: large urban areas (with a diverse workforce, existing infrastructure, ideas that come from outside the industrial sector) can serve to attract firms and spur growth. However, the 0.10 level of significance indicates that while urbanization economies are present, they may not the best predictor of growth or most influential factor. The reason for this significance level may very well come from two distinct growth processes occurring in the United States during this time period. The evidence from all models thus far indicates beta convergence to be occurring during the time period. The growth of Southern states can account for this, as their comparatively low wages made them an attractive for filtering down. However, in the urban areas, especially in the Rust Belt and West Coast, growth continued despite their comparatively high wages. Product Cycle Theory can again help explain this growth process, as this theory suggests that urban areas will exhibit Jacobian externalities that generate the innovative ideas that transform into the new products which produces the greatest profits. The other significant predictor is the distance of the population center to the nearest completed interstate expressway. This predictor has a negative beta, significant at the 0.01 level. This suggests that the further the population centers of a state are from a major expressway, the harder it was for the region to grow during the time period. A simple explanation of this result deals with the spatial margins of profitability, where firms simply choose to locate in profitable regions that have basic access to both labor and product markets. Since transportation costs are a critical factor in the costs of production (at least in the fourth Kondratieff wave), profit maximizing firms should seek to minimize it. Highways offered a new, cheap, and quick network for short and medium haul shipping, and places without access were at a distinct disadvantage. While this is the simplest explanation and holds theoretical validity, it gets complicated when the location of transportation investment in 1970 is noted. Places of importance in the 1970 economy appear to have received attention first, possibly creating a path dependence question of whether or not places that were already well poised for future growth received highway attention first, a situation similar to Krugman's (1991) "locking in" of increasing returns and investment. Also of note in the state model is the lack of significance of other predictors at the state level. The closest of the non-significant predictors is the Right to Work status of the state, which has a p-value of 0.122, approaching significance at the 0.10 level. With the positive beta, this indicates that at the largest level, firms are attracted to current low wages, instead of the governmental effort to keep wages low. What is attractive of the governmental efforts, however, may be the other benefits of weak collective bargaining power, such as a decreased risk of work stoppage that can keep production costs low. The current growth is focused on the wages the region can offer now.

At the EA level, the strength of convergence is significant at the 0.01 level. In addition to 1970 PCPI, additional significant predictors include the Location Quotient for FIRE, percentage of population that lives in a RTW state (since EAs cross state lines), and the population of the Economic Area. The theoretical framework behind each of these predictors is rather straightforward and fits well with both the theoretical basis of convergence theory and the results of the bivariate model. For the FIRE specialization, the coefficient is positive and has a p-value of 0.014, which is significant at the 0.05 level and nearly significant at the most stringent level. The positive value indicates that EAs with a comparative concentration in the FIRE sector tended to grow faster than the EAs which needed to import FIRE activity. This is consistent with the effects of localization economies, where the benefits of similar industries clustering together in a particular region contribute to growth. In this case, Economic Areas that specialized in the FIRE sector, a driver of the fifth Kondratieff, seemed well positioned to take advantage of that early specialization and use it for continued growth . Urbanization benefits are present through the significance of the size of the 1970 population. With a positive coefficient in the model, EAs with larger 1970 populations also had a larger PCPI change. This also is consistent with Jacobian externalities, where simply being in a large urban area offers benefits external to the firm, as discussed in the state model. Of interest here is that urbanization benefits show up through population instead of the urban-rural mix in this model. A possible explanation for this is the functional nature of Economic Areas. Since they are all designed around an urban area, no economic area truly lacks urban aspects. Thus, population size may have better captured of the variation and urbanization effects that occur at this level of aggregation. The final significant predictor is the percentage of the EA population that lived in a RTW state. The positive beta for this variable indicates that as the population of the Economic Area living in a RTW state increased, the PCPI growth rate did as well. This is suggestive of an aspect at the core of the convergence process; regions with lower wages growing faster than regions with higher ones. Right to work legislation places a de facto price ceiling on wages and employee benefits by minimizing the of collective bargaining power of workers. However, at the state level, RTW status only approached significance, but did not cross the 0.10-level threshold. Here it does. At this smaller level of aggregation, there are more observations, and in turn a greater degree of variation of change, as well as more significant predictors. What this implies is that RTW status is not enough to cause growth and draw investment on its own; if it was, state level results would have been significant. But, when it is considered in conjunction with other factors, its importance increased. In other words, RTW status was not enough to induce a firm to locate to a region without other necessary factors of production, some of which, such as industry mix also limit wages. However, once those are in place, growth was attracted to locations with the likelihood of continued low wages. But, the future promise of low wages only entered the discussion if the region is currently profitable. Finally, distance to a completed interstate highway did not come back significant, which is a departure from the state model. This, however, is not very surprising given the nature of the variable. Most of the values are 0 of 15, indicating that they already had close proximity to interstate access, since interstates connect major cities. There simply is not the variation needed for this to be a particularly useful predictor at this scale.

County-level OLS models offer further insights to the results of the state and EA models. Again, 1970 PCPI is significant at the highest confidence level. The additional predictor variables returning as significant are consistent with the results of the other two scales; there is evidence of urbanization economies, localization economies, and the importance of connectivity. Similar to states, the benefits of urbanization economies are reflected through a positive urban-rural mix coefficient, significant at the 0.01 level. Again, this would indicate the role that a large urban center has, and the benefits it can offer have on long term growth. What is interesting behind this result is that the capture of urbanization effects returns to the continuum variable. This may also be explained by the nature of the aggregation sizes, counties as political units and EAs as functional ones. With counties, there is no natural tie to an urban area, so it is possible to have a truly rural county, and in the largest of the urban areas, the core and non-core counties will have large values. Thus, there is a wider degree of variation in this variable and if urbanization counts, it shows up strongly on both ends. Further evidence of localization economies is shown through the significance of the Location Quotient for services. In a sense, this is a departure from the other scales where localization benefits occurred through the specialization of the FIRE sector, however it may not be that much of a departure. In 1970, the FIRE sector was relatively small in the national economy, with relatively few places that truly specialized in it, as the spatial impacts of deregulation had yet to be felt. At the county level, that sparseness is magnified. While states and EAs will capture the spillovers to a region as that small sector would grow, counties likely will not. So, while the FIRE specialization would show up in the county where the firms were located, it would not be taken in to account for the spillovers it would cause in the neighboring counties as the sector expanded, thus hurting its ability as a predictor at this scale. However, the service sector appears to be a reasonable proxy in this case. Since services were much more developed in 1970, the LQs appear to capture the areas with well-developed producer services and personal services to both capitalize on the growth of the FIRE and other sectors. Services are also known to be relatively elastic in regards to income. So, in theory, places with a well-developed service infrastructure should be the places with the income base to support them. Thus, even in places that did not develop the FIRE sector specialization until after 1970, for it to develop, an existing service sector would serve as an incentive for firms in that sector. In addition to income, urbanization, and localization effects, RTW status and connectivity returned as significant. Both returned in the expected direction; negative for connectivity and positive for RTW. The connectivity variable is relatively straightforward, as distance to a completed interstate highway increased the rate of growth decreased. Thus, the spatial margins of profitably show further evidence of playing a role in firm location, and in turn, regional growth, through the latter part of the 20th Century. So, while firms are footloose, they may still be bound to regions of profitability based on transportation costs. RTW classification is significant and the coefficient is positive, reflecting the role that the de facto wage ceiling at the regional and local level. Similar to the EA regressions, this only became significant with additional significant predictors, indicating that RTW only becomes significant when other desirable traits are in place and a generalized regional location has been selected.

In terms of model diagnostics, the OLS models also display similar problems to their bivariate counterparts. For states, residual normality and constant variance remain problematic. The Jarque-Bera test for residual normality has a p-value of 0.04, which is significant at the 0.05 level, but not at 0.01. The Breusch-Pagan test for heteroskedasticty also has a p-value of 0.04, reflecting the borderline performance of the state OLS model. The EA OLS performs slightly worse, passing the Jarque-Bera test, although heteroskedastic residuals remain. The county level model performs the worst, as it fails both diagnostics. Again, this is similar to the expectation of model performance coming out of M.A.U.P. theory, as model performance here has a positive relationship with the aggregation size of the data. Further evidence of these problems comes to light when the spatial diagnostics are employed. The Lagrange Multiplier tests first indicate that there is a great degree of spatial dependence in these models as no scale passes the LM tests. The LM Lag test is most significant for states and EAs, while LM Error is most significant for the county model. This indicates an important point to this dissertation: that the same modeling approach may not be prudent for convergence testing. Here, the underlying spatial structure and influence of the dependent variable is different across aggregation size. For states and EAs, the growth of an areal unit is directly related to its neighbors, while all that can be said at the county level is that there is an underlying spatial association among error terms.

Further insight on the spatial structure can be gleaned from an analysis of the LISA cluster maps of the model residuals displayed in Figure 18. For states, two broad regional clusters can be identified; the northeast and the west. Notably missing from the state map is the cold cluster in the Rust Belt that was present in the bivariate model. With the remaining state level clusters, another noticeable difference from the bivariate results is the introduction of spatial outliers. This offers an immediate departure from the bivariate model, where the clusters were all cold spots. Here, the clusters are a mix of cold spots and spatial outliers. The cold spot in the southwest is consistent with a cold

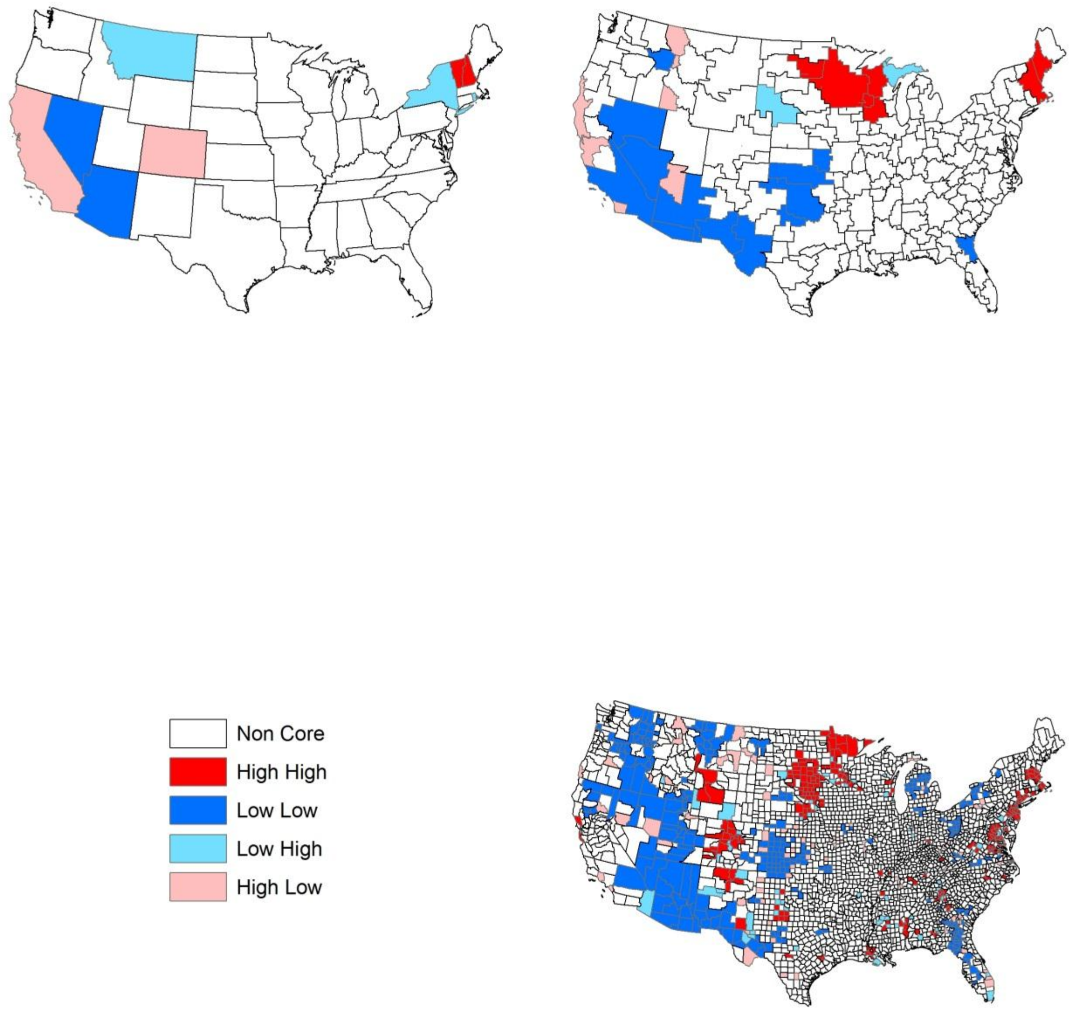

Figure 18: Multivariate OLS Residual LISA Clusters

spot in the same location in the bivariate residuals. However, the spatial outliers indicate that the additional variables created spots where the model significantly under predicted in a sea of over prediction. The outliers, California and Colorado, are places with large urban centers that hold a unique focus on new technology and higher income service sector employment, indicating that in these places the unique economies in the states may have allowed for the actual growth to be much greater than would have been predicted, even after the accounting for economic structure. Possibly operating under similar forces, a hot spot centered around Vermont and New Hampshire, work in conjunction with a low-high outlier centered on New York to create a region of under prediction in the northeast. Both of these regions are similar to the results from the bivariate model, where places with a specialization in technology (New England and Silicon Valley) are surrounded by places that did not receive spill over benefit (upstate New York). This lack of spill over is reinforced by an analysis of the EA and county LISA clusters. Hot spots show up along the Bo-Wash and Silicon Valley regions at both scales, suggesting an inability of the model to fully capture those unique urban knowledge economies. These outliers are then surrounded regionally by places that underperformed, such as upstate New York, or the large rural counties of the west. This suggests that even through these hotbeds of tech activity helped serve as drivers in the modern economy, they were not able to pull large regions in to economic prosperity if other factors, such as urbanization or localization factors were not in place.

As a whole, the multivariate model offers some additional insight in to the regional convergence question. Additional variables improve the explanatory power of the model, however they do not do enough to allow for all models to pass residual diagnostics which indicates that an additional force may be influencing growth. These diagnostics point to a few key points worth noting before moving forward. First, additional variables improve model fit, as expected. However, the modest improvement in model fit suggests that none of the variables are quite as important as 1970 PCPI in predicting PCPI change. The significant predictors are those theorized to be important in the residual analysis of the bivariate chapter; urbanization, localization, and public policy. The importance of these factors, especially the urbanization and localization effects, can be seen in the LISA cluster maps as the extent of the clusters have decreased versus the bivariate model, reflecting the improved model fit. However, the remaining clusters point to the second important finding of this OLS results; specialized urban areas remained as LISA clusters. The areas of under prediction tend to be focused around the urban areas that are driving the high tech/knowledge economy, such as San Francisco and Boston. These are areas that are true outliers, as the growth of these areas is unique to their particular circumstances. In the western cold spot, the slow growth in these areas was not fully captured by the urban or local scores, indicating a larger regional process involved. As such, the effects driving these significant spatial residuals may be best captured through a spatial model. If captured, these effects should also drive non-spatial diagnostics in to compliance.

First Order Spatial Models

Taking the LM results from the previous section, the spatial models are specified as (Equations 23 for states, 24 for EAs and 25 for counties):

$$C_i = k = \beta * SqrtPCPI_i^{1970} + \beta * RTW_i^{1970} + \beta * P_i^{1970} + \beta * SqrtR_i^{1974} + \beta * C_i^{1974} + \beta * SqrtLQS_i^{1970} + \beta * SqrtLQFIRE_i^{1970} + \beta W\lambda + \epsilon \tag{23}$$

$$C_i = k = \beta * lnPCPI_i^{1970} + \beta * lnRTW_i^{1974} + \beta * lnP_i^{1970} + \beta * R_i^{1970} + \beta * C_i^{1974} + \beta * lnLQS_i^{1970} + \beta * lnLQFIRE_i^{1970} + \beta W\lambda + \epsilon \quad (24)$$

$$C_i = k = \beta * SqrtPCPI_i^{1970} + \beta * RTW_i^{1970} + \beta * P_i^{1970} + \beta * R_i^{1974} + \beta * C_i^{1974} + \beta * SqrtLQS_i^{1970} + \beta * SqrtLQFIRE_i^{1970} + \beta W\epsilon + \mu \quad (25)$$

Where:

$PCPI_i^{1970}$ is 1970 PCPI in location *i*

RTW_i^{1970} is 1970 Right to Work status in location *i*

P_i^{1970} is 1970 population in location *i*

R_i^{1974} is 1974 USRA rurality score

C_i^{1970} is 1970 connectivity in location *i*

LQS_i^{1970} is the 1970 Location Quotient for Services in area *i*

$LQFIRE_i^{1970}$ is the 1970 Location Quotient for FIRE in area *i*

W is the spatial weight matrix

λ is the spatial lag term

ϵ is the spatially autocorrelated error term

The results of the first order spatial models are shown in Table 20. At first glance, a few things become apparent. First, the-log likelihood at each level of aggregation increases versus the OLS model. This helps to reflect the importance of spatial effects in the convergence process as simply adding a spatial variable significantly increases model explanatory power. The importance of these effects is further reflected in the coefficients and p-values for the spatial variables. In each model, the coefficient has a positive value, indicating that an increase in the growth rate of an area's neighbor will produce a positive growth rate for itself. The p-values for the spatial variable are all significant at the 0.01

level as well, indicating their importance in the growth model. This importance is further reflected in the model diagnostics. The first order models passed diagnostics at all scales, which would suggest the spatial effects captured the factors leading to heteroskedastic residuals. Even at this most general level of analysis, this first order conditional convergence spatial model appears to be the best fitting model run thus far in the dissertation.

Table 20: Multivariate First Order Spatial Model Results

	State	Economic Area	County
Log-Likelihood	-180.99	-684.28	-14354.34
Breusch-Pagan	7.27 (0.40)	18.22 (0.011)	6.88 (0.44)
Constant (P)	117.54 (0.00)	606.04 (0.00)	281.47 (0.00)
1970 PCPI (P)	-0.69 **(**0.12**)**	-61.31 **(**0.00**)**	-1.96 **(**0.00**)**
Population (P)	-0.0007 **(**0.70**)**	0.007 (0.00)	-0.001 (0.70)
LQ Service (P)	22.27 (0.25)	7.01 (0.12)	4.60 (0.02)
LQ FIRE (P)	-3.34 **(**0.87**)**	8.88 (0.02)	0.75 (0.24)
Right to Work (P)	5.13 (0.12)	0.59 (0.01)	8.19 (0.00)
Connectivity (P)	-0.14 **(**0.01**)**	-0.01 **(**0.59**)**	-0.03 **(**0.08**)**
Urban-Rural (P)	0.61 (0.19)	0.012 (0.30)	0.051 (0.00)
Spatial (P)	0.48 (0.00)	0.35 (0.00)	0.44 (0.00)

In terms of the individual models, the convergence evidence is mixed. At each scale, the coefficients for 1970 PCPI are smaller than in the non-spatial models suggesting the omission of the spatial variable biases regression coefficients. The inclusion of spatial effects actually takes away some of the predictive power of 1970 PCPI. This is not surprising given the fact that an additional predictor can capture more variation as displayed by the decrease in coefficient size when the model moved from unconditional to conditional. This suggests that some of the variation initially captured through 1970 PCPI is now captured through the spatial lag or error. When framed with convergence theory and results of previous chapters, it is not surprising; PCPI is known to be highly spatially autocorrelated, and low levels of initial income are theorized to cause faster rates of growth. So, while the spatial variable will capture the PCPI change of a neighborhood, it can be tied back to initial levels of PCPI. However, the better fit of the spatial model indicates that some change originally attributed to 1970 PCPI may actually a result of a more regional income association. As is the case with the OLS model, the strength of convergence increased as aggregation size decreases with smaller scales reflecting the convergence process more clearly. In fact, this is further supported by the lack of significance of 1970 PCPI in the state regression. While, still a negative value, the p-value of 0.124 is not significant, a result similar to the bivariate state model; a result that suggests convergence is best studied at smaller scales.

Once the spatial effects are taken into account, the initial income variable is not the only variable to see a change in significance. In the state model, the only variable to retain significance is the connectivity variable, again suggesting the importance of the spatial margins of profitability. This is in contrast to the urban-rural continuum variable which lost statistical significance in the spatial model. A possible reason again lies with the masking of the data. With more variables significant at smaller scales, a lagged dependent variable may be the best predictor in these larger area models. For the EA model, we see a similar result in that p-values have become slightly, though consistently, larger. However, none of the variables manage to lose significance, implying a bit more stability in results than in the state model. A similar result can be seen in the county model. All predictors that are significant in the OLS model are significant in the error model, although to a lesser degree. Worth noting is the change in significance that occurred to the connectivity variable. Here, although still significant, its p-value moves from 0.01 to 0.08, moving it from the strongest level to the weakest level of statistical significance. In this case, it may be that 1970 PCPI and connectivity are picking up similar aspects of spatial autocorrelation, since income change and distance to a major highway are both highly spatially autocorrelated variables. So, the addition of the error variables takes away from some of what was captured in the buffer distance variable.

For model diagnostics, the spatial models perform much better than their OLS counterparts. In the OLS models, a consistent problem was heteroskedastic residuals. No OLS model passes the Breusch-Pagan test at all levels of confidence, and the EA model outright failed. Once the spatial term is included, that diagnostic problem is fixed at all scales, as no Breusch-Pagan result is significant. This indicates that the additional variables and spatial component takes care of the heteroskedacity problem, indicating model validity. Additional predictors can be added, but none are needed for the model to be valid.

In terms of LISA clusters (Figure 19), there is an across-the-board improvement versus the OLS residuals. For states, only four (New York, California, Montana, and Nevada) return as the center of clusters. More importantly, the first three are spatial outliers in a similar vein as in the OLS model indicating consistency with the OLS model. This suggests the causes for these outliers, such as the island of development in California or the detrimental effect of upstate New York, are truly outlier effects. In the EA model, there are hot spots in New England and a spatial outlier high-low in the coastal areas of California, both of which offer further insight to the outliers in the state

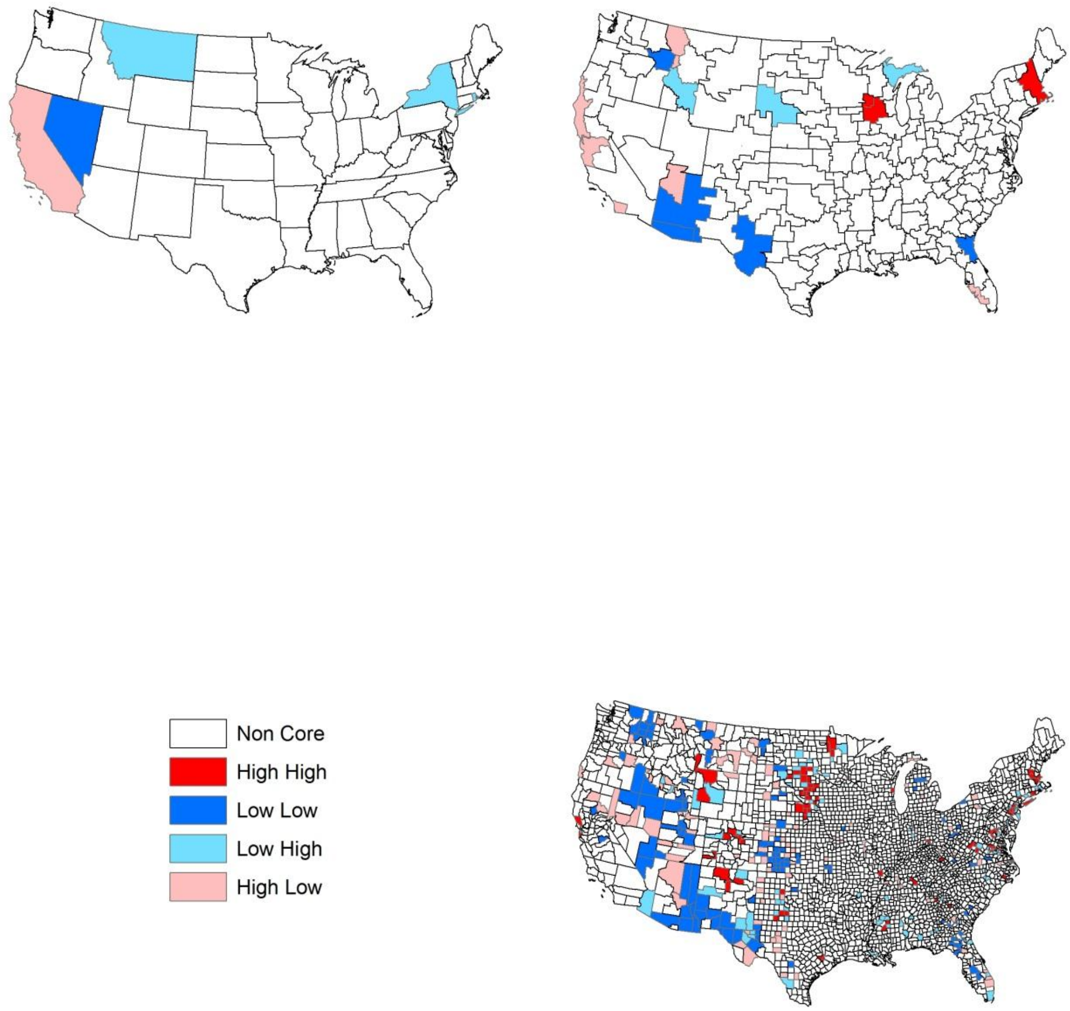

Figure 19: Multivariate First Order Spatial Model Residual LISA Clusters

model. Both of these clusters are present, though larger in scope, in the OLS model. The implication is that the spatial model accounted for a lot of the processes leading to the regionalization effect. What is left are the places where forces are unique enough to be the true outliers driving the outliers in the state models The coastal areas of wealth are areas that would have benefited directly from the technology sector in the fifth Kondratieff (Silicon Valley) or benefited from being a part of a cluster (New England to Boston's tech coordinator). Further in the EA residuals, we see clusters of low-low in the southwestern United States, and a region of intersecting poverty and wealth in the Idaho-Washington area. As a whole, in the residuals, the LISA Clusters tend to be isolated, suggesting a validity of the model. The county residuals follow the trends of the state and EA clusters, just showing more detail. Across the board, the clusters are smaller in extent than in the OLS model, again implying a superiority of the spatial model at this level as well. On the east coast, there is a relatively large cluster centered around Boston, and its west coast counterpart of Silicon Valley is present, again suggesting the uniqueness of those regions and their growth process. The other noticeable trend in the clusters is the smattering of cold spots and high-low outliers in the mountain regions, and a hot spot in the northern plains. The northern plain hotspot is a consistent one in the county maps, though smaller in scale than in the OLS map. Of greater interest, however, is the western cold spot/spatial outlier mixture. In the OLS residual map, this region was larger and a uniform hotspot. Here, the extent shrank, and there is the introduction of high-low spatial outliers, counties where the model significantly under predicted versus its neighbors over prediction. Compared to the standard deviation map of PCPI change, the high-low outlier counties here are ones whose growth was slow due to their higher initial incomes, but who did not grow as slowly as their neighbors. These are also counties who appear more rural than their neighbors, which is actually consistent with the regression models, where higher urban-rural continuum scores predicted higher growth. In these cases, there are rural areas which did not grow as slowly as their neighbors, so the regionalization we see may be a function of their location and neighbors. In all of these regions, these data are very sensitive to the influence of population. Given their relatively low population in 1970, any population change could have a drastic effect on PCPI, and in turn, the model.

In this section first order spatial effects are added to the conditional model used in the OLS section. A spatial lag model is used for states and EAs, and a spatial error is used for counties. The spatial models improved the model fit and diagnostic performance of the OLS models. Consistent with the bivariate analysis, the addition of the spatial component makes 1970 PCPI insignificant as a predictor at the state level. Otherwise, the models remain consistent with convergence evidence and significant predictors. However, the addition of the spatial component generally reduced the coefficient magnitude for each predictor, although this is not a surprising result.

Second Order Spatial Models

In all previous models, spatial effects have been shown to be quite prominent, as the spatial models improved model fit and diagnostic performance versus their OLS counterparts. In this section, the spatial weight matrix used in the conditional model is expanded to second order neighbors, and the regression models and analysis are rerun. To begin with, LM tests using the second order weight matrix are applied to the OLS regressions to determine if spatial dependence is a problem in the regression and what type of model should be applied to correct for it. Results are displayed in Table 21.

Table 21: Multivariate Second Order Lagrange Multipliers

Scale	State	Economic Area	County
LM Error (P)	0.59 (0.44)	1.70 (0.19)	368.02 (0.00)
LM Lag (P)	0.15 (0.69)	2.49 (0.12)	225.67 (0.00)
Robust LM Error (P)	0.82 (0.37)	0.06 (0.80)	145.68 (0.00)
Robust LM Lag (P)	0.39 (0.53)	00.85 (.36)	3.33 (0.07)

The LM results offer a very interesting result, the only level of aggregation that displays spatial dependence is the county level. The loss of significance for states is consistent with the bivariate model and likely from a similar cause. What is of interest is now the lack of significance for the EA level of aggregation. To be sure, the lack of significance is slight, as the p-value for the Robust LM Lag is 0.12, only 0.02 from significance. However, even if significant at the 0.10 level, it would still be much less of a degree than both the bivariate and first order results. This result provides us with two bits of information. First, it adds additional evidence to the results from the bivariate model that suggest that different spatial weight matrices can yield differing results in the convergence test. Here, again, if the weight matrix is improperly defined, the spatial dependence inherent in the model will be missed. In this case, as is the case in the bivariate approach, it appears that a first order definition is the more appropriate definition.

Since only the county model returned significant, it is the only model run. Regression results are displayed in Table 22. Compared to the first order and OLS regression, this county model is the middle ground in terms of model fit. The first order model displays the largest log-likelihood, the second order model is slightly smaller, and the OLS model is off by itself. This offers support for the argument in the LM discussion where it appears that the first order spatial weight matrix is the appropriate calibration. Further evidence comes from the Breusch-Pagan test, where the second order model passed, but not as strongly as the first order. So, the second order weight matrix captures enough of the regional effect to provide constant variance in the residuals, which is an improvement over the OLS model. However it simply does not do as good of a job as the first order model.

There is evidence for beta convergence in this model, with a negative coefficient (-1.88) on 1970 PCPI, which is significant at the 0.01 level. Compared to the OLS and first order results, the evidence here is weakest in terms of coefficient size.

Table 22: Multivariate Second Order Spatial Model Results

Scale	State	Economic Area	County
Log-Likelihood	N/A	N/A	-14.387.95
Breusch-Pagan	N/A	N/A	8.49 (0.29)
Constant (P)	N/A	N/A	276.80 (0.00)
1970 PCPI (P)	N/A	N/A	-1.88 **(**0.00**)**
Population (P)	N/A	N/A	0.001 (0.47)
LQ Service (P)	N/A	N/A	4.66 (0.019)
LQ FIRE (P)	N/A	N/A	0.82 (0.21)
Right to Work (P)	N/A	N/A	7.46 (0.00)
Connectivity (P)	N/A	N/A	-0.02 **(**0.10**)**
Urban-Rural (P)	N/A	N/A	0.06 (0.00)
Spatial (P)	N/A	N/A	0.51 (0.00)

This indicates that the spatial variable may be responsible for more of the predictive power of the model than in the first order model. This is confirmed with the larger coefficient for the error term. However, even though spatial effects count for more in this model, the decrease in model fit indicates that the use of the spatial variable as a predictor in that magnitude may not be the best specification. The other significant predictors in this model include the LQ for Service employment, RTW status, connectivity and urban effects. These predictors are also consistent with the significant predictors in the first order conditional county model, so the slight change in error term specification did not change the model all that much, consistent with the moderate change in model fit. In addition, the Breusch-Pagan results indicate the model passes the residual variance test. In short, the second order model appears to work, although not quite as well as the first order model.

The LISA cluster map of residuals is displayed in Figure 20. Again, residuals are only mapped at the county level. In terms of clusters, the most prominent region is the western United States cold spot. This cold spot is one that has remained consistent in models, scales, and spatial weight matrix definition. What is unique about the cold spot in this second order analysis is how it compares to the first order county residuals. One consistency is the presence of urban counties, especially in California, serving as high-low spatial outliers. In California, the home counties of San Francisco and San Diego serve as the core areas of high-low outliers. In the southwest, the role of the urban areas is slightly different, as the urban areas serve as the rings in low-high outliers. This is most notable in Arizona, where the second order neighbors to Phoenix and suburbs are the low-high outliers in the otherwise cold counties in the southern portion of Arizona and New Mexico. A similar pattern appears in Colorado, where the urban central part of the state serves as the centers to small hot spots and outer rings to low high outliers. Otherwise, the large cold spot extends through the mountain region, as is the case in the

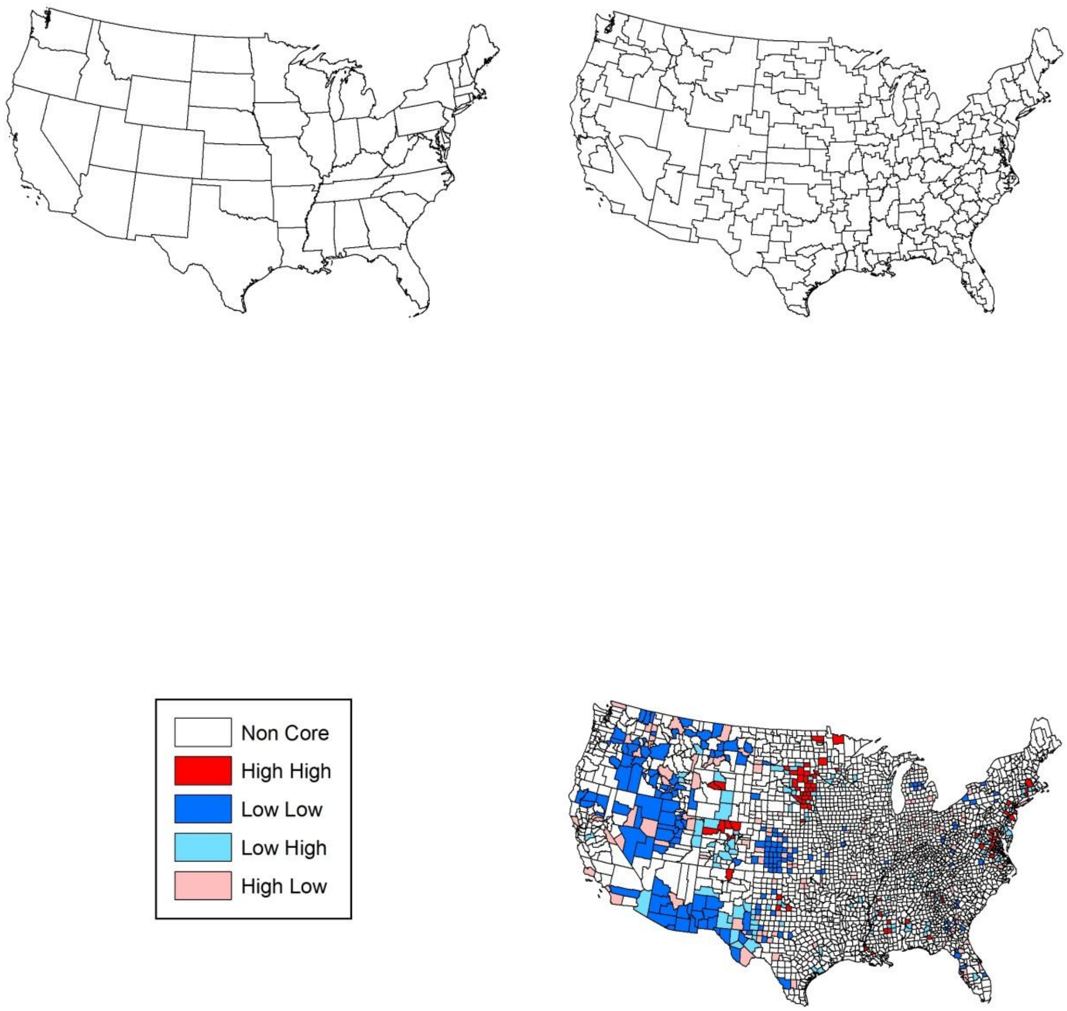

Figure 20: Multivariate Second Order Spatial Model Residual LISA Clusters

other models. Other clusters, such as the upper plains hot spot and east coast hot spot, are present in the first order and bivariate model. But, as was the case in the bivariate model, the extent of these clusters is slightly less than the first order residual clusters, as the second order weight matrix requires there to be a slightly larger spatial effect present to be detected. In the Rust Belt, there is a smattering of low-low counties and high-low outliers. The low-low clusters are expected in the Rust Belt, however they are largely contained to individual counties, so the true cluster is much smaller than the regional effect noted in the OLS model. The high-low outliers are a bit more interesting as they tend to be focused.

In this section, a second order spatial weight matrix was applied to the multivariate conditional model. Immediately, the impact of this specification is seen; only the county level model indicates the need to use a spatial model. This result offers evidence for two main points of this dissertation. First, it provides an example of the role the aggregation plays in convergence model results. Here, with a slightly mis-specified model, the expected spatial dependence disappears at two of the three levels of aggregation. In addition, it reflects that the spatial effects known to be present in income are highly localized. Thus, they can still be captured at the county level, but not at the state or EA level when tested at a second order relationship. In addition to the spatial and scalar effects, other regression predictors do not change much. Initial income levels still appeared to be the strongest predictor, with urbanization, localization, and RTW status still playing a role.

Conclusion

In this chapter, a multivariate conditional convergence model was applied to state, EA, and counties using OLS, first order, and second order spatial models. Regression results were compared across scales, weight matrices, and against the bivariate model of the previous chapter in terms of model fit, model diagnostics, and predictor strength. The goal of this chapter was first to determine if a conditional model did a better job in predicting income convergence than the unconditional model of the previous chapter. It did. Across the board, log-likelihood values were smaller than the bivariate models at each scale. Additional goals of this chapter were then to investigate the additional causes of regional convergence and the impact of spatial and scalar effects on the model results.

In terms of the conditional model itself, the additional predictor variables provided for a stronger model fit. The increase in model fit was slight, reflecting the importance of 1970 PCPI as the main predictor variable. That suggests the theoretical background of the convergence process is solid; investment appears flow from regions of high income to regions of low income. However, the additional predictors play a larger role in controlling for the outside forces that can cause diagnostic problems, such as public policy or employment specialization. This improvement was reflected in all of the non-spatial diagnostics, as the spatial models all passed the Breusch-Pagan test. In the LISA cluster analysis, the multivariate models provided a drastic improvement over the bivariate model. While the OLS models displayed significant clustering in regions similar to the bivariate models, the extent of the clusters were not as large as the bivariate model. This suggests an ability of the additional variables to remove all but the strongest of the outliers. In terms of the individual predictors, the hypothesized predictors were generally significant, though that significance varies by level of aggregation. Urbanization effects were shown to be important through the significant positive coefficient for population at the state and EA levels, while the urban-rural continuum was significant at the county level. The significance and direction all indicate that economic growth tended to be focused in areas where there were urbanization effects at work. Localization economies were shown to be important, as FIRE specialization was a significant predictor at the state and county level, while service specialization was significant at the county level. These results suggest that places where there was a focus on the higher knowledge specializations were able to grow faster than those without. In addition, the level of connectivity is significant at all scales, reinforcing the idea that the more connected locations are more attractive to firms relocating and new firm formation. Finally, RTW status also came back as important at the smaller scales, and borderline at the state level. This suggests that growth tended to occur in places with a false wage ceiling in place. However, the true significance came back at the smaller levels of aggregation, where the implication is that for the firm that has already decided on a region, it is more likely to pick a location within that region with RTW status if it is available. However, the direction also may point to an unexpected result, where the RTW locations grew faster than non-RTW areas, a result which would be the direct opposite of the planned effect of these policies. This is an interesting question which would necessitate further research as it is outside of the scope of the models used in this dissertation. However, possible explanations for that impact are that regional growth simply puts upward pressure on wages, even with the de facto price ceiling in play, or that firms may be attracted to RTW locations due to the weak collective bargaining power weakening other risks and costs to the firm such as work stoppage risk or additional benefit packages.

Outside of the identification of additional causes of regional growth, one of the most striking results of this chapter is the reinforcement of aggregation effects. While the models follow the established and expected pattern of the larger level models displaying greater model fit, when results were compared across scales the results displayed great disparity. In terms of predictors, there was not a uniform display of significance. Just as 1970 PCPI is significant at the EA and county levels in the bivariate spatial model but not at the state level, a similar pattern is displayed with both 1970 PCPI and also the urbanization and localization effects. For urbanization, it is captured at the larger levels through population, and counties through the continuum score. This suggests an ability of the unweighted continuum to more fully capture urban effects, as the unit of aggregation is not tied directly to urban areas, such as the EA, nor can all of the variation be masked such as at the state level. In terms of localization effects, FIRE is important at the larger levels, while service at the smaller level. This may be attributed to the difficulty of capturing the critical threshold of FIRE employment at a small level of aggregation in 1970, so the service sector served as a substitute. Interestingly, RTW status is only not significant at the state level, which is the level of aggregation where the legislation would be passed. This might indicate the legislation was not a direct cause of drawing growth to a state, but rather played a role in the location of a firm once it decided where to locate. In addition, the betas indicate that while RTW legislation can positively impact growth, it is also correlated with locations experiencing faster growth.

In addition to coefficient variation, model fit, spatial structure, and residual diagnostics also show the importance of scalar and spatial effects when compared across the three levels of aggregation. Similar to the bivariate model, and in accordance to the

M.A.U.P. literature, the best model fit came at the largest level of aggregation, and the worst at the smallest. However, the diagnostics paint a different picture. In the bivariate model, the state and county level models both have specification problems while the EA level model performs quite well in terms of diagnostics. The conditional model fixes the specification problems of states and counties and performs well in terms of traditional and spatial residual diagnostics. However, the residual diagnostics got worse for the EA level model, as the heteroscedasticity test is only barely passed. This indicates an area for future work; depending on the type of aggregation, the different convergence processes may be at work. The political levels of aggregation seem to perform best in a conditional convergence model, whereas the functional units seem to perform best in an unconditional model. In other words, when studied at a “natural level”, regions may converge based upon initial income levels. However, when a non-economic structure is superimposed on the processes, external forces need may need to be taken into account.

CHAPTER 8: CONCLUSION

Summary

Convergence theory comes out of neo-classical growth theory and suggests that regional incomes will converge over time. Within this framework, beta convergence is a phenomenon that occurs when regions of initial poverty grow more quickly than regions of initial wealth. Beta convergence is understood and can be tested under two differing theoretical frameworks: unconditional convergence and conditional convergence. Unconditional convergence occurs when regional incomes converge regardless of the underlying regional economic structures. Conditional convergence occurs when regional incomes converge, but only when underlying economic structure is taken into account. The standard test for unconditional convergence, as proposed by Baumol (1986), is a bivariate regression where initial income levels serve as the predictor variable against income change. Beta convergence is present when the beta coefficient is significant and negative. This test has been applied to a variety of regions, scales, and time periods with inconsistent results. One effort to correct for these results is a standard regression technique of including additional explanatory variables to improve model fit and explanatory power. Adding variables to the regression controls for regional economic differences, which then makes the model a conditional test. The additional predictors vary by study. However, they can be broadly classified as controls for labor/human capital quality, urbanization effects, localization effects, governmental investment, transportation access, and savings. In theory, these should solve some of the problems of the bivariate model, however the results of conditional convergence models are still plagued with inconsistencies. For geographers, two clear potential causes for inconsistent model results are spatial dependence and the M.A.U.P., both of which remain relatively unexplored in the convergence literature. Issues related to spatial dependence relate to the fact that spatial data are unique from other data due to their locational attribute. According to the First Law of Geography (Tobler 1970), near things are more related than far things. Applied to regression, this means that with spatial data observations may not be independent of from each other, which can lead to skewed confidence intervals and model failure. In convergence analysis, income is the source of both the dependent and independent variables and is also known to be spatially autocorrelated. Yet, most analyses omit corrections for spatial dependence. The few models that do account for spatial dependence show it as important in terms of prediction and model validity (Rey and Montouri 1999). But even then, the nature of spatial dependence (lag or error) remains open due to inconsistent geographic building blocks used in the analyses. The M.A.U.P. is another potential source of conflicting results due to the variety of scales at which both convergence models have been applied. What is known about the M.A.U.P. is that correlation strength and model fit tend to increase as aggregation size increases (Openshaw and Taylor 1979). Applied to convergence, with the multitude of scales in which the models have been applied, there is great potential for M.A.U.P. effects to influence results. As intuitive as the potential for problems in convergence analysis stemming from these sources may be, the magnitude of these issues is relatively unknown. Spatial convergence models are typically run without regard to aggregation bias, and M.A.U.P. studies are relatively unexplored in convergence. This dissertation sheds additional light on this issue by examining the impact of both effects through a consistent study area and model where spatial and non-spatial models are compared at three levels of aggregation in the United States for the 1970-2004 time period.

In the first section, Exploratory Spatial Data Analysis (ESDA) techniques were applied to 1970 PCPI and PCPI change 1970-2004 for states, Economic Areas (EAs), and counties using first and second order queens neighborhood definitions. Global spatial dependence was positive at all levels and strongest for 1970 PCPI and PCPI change at all levels of aggregation. This universally significant spatial dependence suggests that a spatial modeling approach in convergence analysis is needed. With spatial dependence in both the dependent and main predictor variable, the income observations are not independent of each other, and thus violate an assumption of OLS regression which can lead to both model failure and inflated p-values for predictors. One step further, the local spatial autocorrelation results also provide insight to the locations of the bottom-up and top-down convergence. The 1970 PCPI distribution exhibited a clustering of high values in the Rust Belt and west coast, regardless of level of spatial aggregation. A cold spot of 1970 PCPI was present generally in the Southeast at all levels of aggregation. When these clusters were compared to the PCPI change clusters more convergence evidence appeared. The regional hot spots of initial income levels were a combination of non-core members or cold spots at each scale, all while the Southeastern cold spot became a hot spot. Regionally, this is reflective of the convergence process as there was a clustering of incomes at the initial period, and a clustering of change rates in the expected directions.

In terms of strength of association, the functional level of aggregation, the EA, had the strongest level of spatial dependence indicating that even at a level where economic observations should be independent, they were not. Evidence was weakest at the state level, which runs counter to M.A.U.P. theory where the largest level of aggregation should have the largest correlation coefficient. However, this reflects the spatial structure of convergence; the regional effect appears to be localized. So, for modeling convergence, more insight could be gained from smaller levels of aggregation. This inference was further examined in Chapters 6 and 7.

The second area of analysis was a multi-scalar spatial analysis of the bivariate Baumol-style model. The first step in this analysis (Chapter 6) was a three scale OLS analysis. Here, model fit decreased as spatial aggregation decreased, consistent with M.A.U.P. theory. Residual diagnostics were problematic as only the EA passed the traditional diagnostics. Convergence evidence was strongest at the smaller levels of aggregation, further suggesting a localized regional effect. When tested for spatial dependence, no level of aggregation passed the diagnostics. The structure of spatial dependence for states and EAs was best captured through a spatial lag, while a spatial error model was more appropriate for counties. When spatial effects were taken in to account, model fit improved at all scales. In addition, residual diagnostics improved at all scales although only the EA level model passed all diagnostics. Convergence evidence slightly decreased with the addition of the spatial variable indicating that some of the regional effect was captured in initial income levels, an unsurprising outcome given the spatial dependence of convergence variables. However, the increase in model fit suggests the regional effect was better captured in the spatial model. This suggests that it is not a specific location that draws a firm in the convergence process, but rather a generalized location. Further, the failure of the spatial model to fix residual problems at political levels of aggregation indicated that at these levels of aggregation additional variables were needed. In turn, this suggests that at the non-organic, political level of aggregation the convergence process may be conditional-- a process that suggests growth rates can be influenced by endogenous factors.

In Chapter 7, a multivariate conditional model was run using the same levels of spatial aggregation and neighbored definitions as in the previous chapters. In the OLS analysis, results remained similar to the bivariate results; model fit was in direct relation to spatial aggregation size. It is noteworthy that the additional predictors only marginally improved model fit. This suggests that the forces driving the convergence process may indeed be those unconditional forces theorized and tested by Baumol (1986). That being the case, the role of these predictors may not reflect the impact of economic structure on growth rates. Rather they control for the residual problems additional explanatory variables create. The significant predictors were consistent with growth theory: urbanization and localization effects are important, connectivity matters, with policy variables exerting a marginal influence. With the addition of these predictors, residual diagnostics improved for the political units, but not EAs. When tested for spatial dependence, a similar pattern emerged as in the bivariate analysis. No model passed the LM tests, and a spatial lag was appropriate for states and EAs while an error model was appropriate for counties. Again, model fit improved with the inclusion of the spatial variable. But more importantly, the spatial variables corrected residual diagnostic problems, making all models valid. As was the case with the bivariate model, the inclusion of the spatial variable lessened the significance of the existing predictors. However, none of the p-values crossed the threshold to lose significance, reinforcing their role in the growth process.

Drawing the results of the modeling exercises together, the answers to the primary questions of this dissertation- how space and scale can impact beta convergence test results surfaced. First, both space and scale matter. Spatial effects are of critical importance when it comes to the validity of convergence models. In both the conditional and unconditional models, OLS models failed tests for spatial dependence of residuals. Observations were not independent and confidence intervals were skewed. When spatial effects were taken into account, model fit improved across scales and models. Further, the addition of spatial variables caused regression coefficients and p-values to get smaller. In fact, at the state level, the spatial variable completely removed the significance of 1970 PCPI, suggesting that incomes are not converging at the state level. This result points to a key finding of this dissertation: spatial effects are of critical importance in terms of model validity, and with everything else being equal, a spatial and non-spatial model can produce different results in testing for convergence. Given the inconsistency of spatial effects models in the convergence literature, this result helps explain incongruent convergence results.

Secondly, all things being equal, convergence models are especially sensitive to M.A.U.P. effects. In both models, convergence evidence varied by scale with the strongest evidence coming at the smaller scales. This is a very important finding. With convergence models tending to be very similar, stemming a common father in the Baumol (1986) model and applied universally, these findings highlight one possible reason for model disagreement. With all things being held equal other than spatial aggregation, convergence strength and significance varies. Aside from simply providing a powerful example of a source for model disagreement, these results question the appropriateness of traditional approaches to modeling and testing for convergence. Not only did the models present varying evidence for convergence, the treatment of the variables different by model requiring differing transformations to optimize model fit. The need for differing transformations suggests that slightly different processes are occurring at different levels. Here, at political levels of aggregation, the conditional models outperformed the bivariate models in terms of model fit and diagnostics. However, the diagnostics for the functional EAs indicated better model performance in the unconditional model. Thus, depending on the type of spatial aggregation, a different model may be needed to capture spatial effects.

At political levels of aggregation, the important predictors also shed light on some of the endogenous forces that can be used by governments to manage growth. Both urbanization and localization effects are important. Although a government may not be able to legislate its way to urbanization, it can help target its employment specialization through industrial recruitment and human capital investment. In addition, from another policy perspective, factors addressing the costs of doing business in a community also appear to influence results. Transportation connectivity was of strong significance, where highway access had a positive impact on growth, reflecting the importance of the spatial margins of profitability. Thus, transportation investment may be a prudent investment for the region seeking economic growth. In addition, the impact of RTW legislation was significant, but at the smaller levels of aggregation. This implies that although passed at the state level, RTW may not serve to draw firms to states per se. Rather, firms may make locational decisions at the regional level and those regions where RTW applies are implicitly associated with lower levels of unionization. This, in turn, sets the stage for regional competition, as local governments may begin to pass legislation to compete with each other in an effort to attract those regional firms. However, this result is still too preliminary to make policy decisions, and will need more research, specifically at the firm level. The potential for local government competition sets the stage for another important practical application of these results- evidence for the case of regionalism in governance.

The Case for Regionalism

Regionalism, as an approach of governance, generally refers to the framing of governance decisions and actions at a regional level, which is dependent on a shift of authority from smaller and larger levels of aggregation to regional scale governments (Foster 2001). Inter-jurisdictional efforts can focus on most any governmental responsibility, but the push for Regionalism generally applies to following areas; environmental regionalism, fiscal regionalism, economic regionalism, political regionalism, equity regionalism, growth-based regionalism, cultural regionalism, and ad hoc regionalism (Foster 2001). While these differing areas of interest cover a wide range of special interests, an overarching theme involves its application to economic issues. Growth-based regionalism, economic regionalism, fiscal regionalism, and equity regionalism are all special interest areas that deal with fundamental economic issues covering the generation and distribution of wealth. The focus on the generation and distribution of wealth and resources has been at the center of Regionalism historically, though the goals of the movement have shifted over time. Historically, the main push behind the Regionalism school of thought relates to the benefits that can be achieved via the regional promotion of an equitable and efficient distribution of wealth and resources (Norris 2001). However, more recently, the goal of Regionalism has shifted towards the promotion of regional competitiveness in the global economy (Barnes and Ledebur 1998; Norris 2001). In the time period leading up to the birth of this new Regionalism, the built environment of cities continued to grow and sprawl. By the 1990s, there had developed great disparities in both services and amenity provision, but also economic health, and the demographic makeup between urban centers and their suburbs. For the traditional Regionalists, this disparity would have served as a means to pursue more equity-based and redistributive policies. Typically, these policies and arguments would have been met by proponents of Tiebout-esque fragmentation and the public choices it advocates (Weaver et al. 2000). However, instead of the traditional equity based arguments, Regionalism proponents have now found a case for Regionalism in the promotion of local governments own self-interests (Swanstrom 2001, Voith 1998). This new argument is centered around both a recognition the local economy is faced with much more intense competition globally than ever before, and growth in research showing that metropolitan regions with fewer disparities between central cities and suburbs tended to grow faster than those with greater disparities (Foster 2001). This global competition is not from states or municipalities, but rather cities and their surrounding communities that supply labor and capital regionally and act as one unit in the global market, or what Peirce (1993) calls citi-states. The fact that these successful citi-states are acting regionally is not surprising given that even with the fragmented labor markets, consumption markets, and capital markets are indeed regional (Swanstrom 2001). In other words, the competition from international regions may force U.S. regions to recognize that "we're all in this together" (Foster 2001). Or, in terms of spatial relationships, how your neighbor fares in the global economy affects how you fare, a position which has been stated many times in this dissertation.

The results in this dissertation and their theoretical implications align well with the arguments behind the new Regionalism movement. At the most fundamental level, that is where the practical application of this dissertation lies-- in providing empirical support for some of the main arguments behind new regionalism. The first area of empirical support for new Regionalism is the significant spatial dependence at all scales related to both growth, income, and the growth models. While this simply reinforces the "in it together" argument, the case for Regionalism is compelling when spatial dependence is analyzed at the smaller scales. The LM results indicate that spatial dependence is strongest with a more compact first order weight matrix instead of a second order neighborhood. In addition, the LM results indicate spatial dependence to be stronger as spatial aggregation gets smaller. These results indicate that spatial dependence associated with regional growth is highly localized in effect; it may be best captured through immediate neighbors, and tapers off relatively quickly in terms of absolute distance. So, the functional economies that are operating do not appear to function at the county or state level, but at the regional/metropolitan level.

The need for this regional approach in policy is also reinforced by the type of convergence process occurring at the level of aggregation. The models for the political levels of aggregation performed best in a conditional model, while the EA growth rates were best modeled with an unconditional model. What this means is that the functional EAs were the shortest and simplest path to explanation, and also the aggregation unit that appeared to capture the unconditional convergence process. With the additional variables, and their significance, proponents of localism might be inclined to incorrectly argue that it was the local efforts (such as employment specialization) that helped spur growth. The additional variables, even if significant, actually account for comparatively little explanatory power. The improvements in log-likelihood values from the unconditional models are marginal and nowhere near the scale that the addition of spatial effects variable captured in the movement from OLS to the spatial model. So, it does not appear that those variables truly drive the growth, rather, they may just control for problems in the residuals that arise when a regional process is zoned to a smaller scale.

Further evidence supporting the regional aspects of economic growth comes from the residual analysis when the county level and EA clusters are compared. At the EA level, the spatial outliers tend to be clustered around urban areas that either drove the fifth Konrdatieff (such as those on the west coast), rural areas in the Plains, or declining urban areas. As a whole, the clusters were few. But, those clusters serve as a point of departure for the clusters of the county models, where Regionalism evidence comes to light. In the clusters of the knowledge economy on the west coast (and the Bo-Wash area at the county level), the core counties of these clusters are generally focused on the urban centers. This is not surprising given the theorized impacts of urban areas on growth. However, in these hot spots where the model under predicted growth, the focus on the urban areas suggests that growth has difficulty spreading out of the county and its immediate neighbors. The urban core and the first order neighbors are those to experience the growth. This implies that the strong relationship between a healthy center city and suburbs serving as the main thrust behind the new Regionalism call may be correct. However, this Regionalism effect appears rather localized, as the Bo-Wash growth is not able to slow the decline in other nearby Rust Belt regions, such as upstate New York. In addition, in the declining Rust Belt areas the spatial outliers take a much more unique role at the county level. The outliers in the Rust Belt tend to characterized by underperformance. What is of interest here are the outlier cluster cores, which are centered on two types of counties; urban areas that actually grew, and suburban counties that grew. The urban areas of growth seem to be those which were relatively new players in the national economy, and thus developed a specialization on the new drivers. However, they did not appear to spill growth over to their neighbors. But, of perhaps greater interest is growth and the role of the suburban spatial outliers. Here, these tend to be the counties in a declining urban area that avoided the decline, with one especially prominent example in the Detroit region. In these clusters, competition for what is left of a declining economic pie amongst the counties suggests that the growth we see may simply be a movement of former center city investment to a particular suburban location, causing growth in those locations. But, it does not represent true growth. Rather, it just represents a regional reallocation as the functional economy still declined.

The effect of competition and redistribution is seen in greater detail through the Right to Work variable. Insignificant at the state level, the level where it would be adopted yet significant at the smaller levels of aggregation, this result suggests that the attractiveness of that de facto price control is not at the macro level, but rather for firms who have made a more localized regional decision. In fact, many of the RTW states are low wage states located in the converging Southeast further reflecting that it was not policy, but other factors that influenced growth at the larger scale.

So, with this empirical evidence in support of the new Regionalism, the direct relevance of this dissertation comes in the impact these results can have on development policy formulation. At the most fundamental level, the "in it together" mantra of the Regionalists receives a great degree of support from the model results in this dissertation. This mantra, however, is in contrast to the traditional factory chasing economic development policies driven by the localization approach discussed by Tiebout (1956). The results here would indicate that local governments should stop competing with each other to attract out-of-region firms. Instead, in perhaps a more unique approach, if local governments could instead work together to create a package of regional incentives, they may be able to create a larger piece of the pie. Once firms are attracted through that regional package, the local governments may then be able to offer local incentives to allow for localized Tiebout-esque sorting. This duel level of incentives and sorting fits with the results of this dissertation and the Regionalism and localism theories. From this dissertation, the model results indicate that firms select a regional location first, and then engage in local sorting based on policy. So, it may not be the local policy incentives that provide the initial attraction to the firm. By making the region as a whole more attractive, all local governments will have more firms and investment to attract through local sorting policies. In addition, this dissertation provides evidence in support of the type of polices upon which regional governments should focus their efforts. For example, the evidence suggests that transportation connectivity plays a role in regional growth. Regional investment in highway construction, or even regional lobbying efforts for highway locations, or regional investment in air facilities, can serve to open a region up to investment. In addition, the models point to the importance of localization effects, but only in the urban areas that had a specialization in the new economy. For example, in Detroit the heavy focus on old Kondratieff Wave industries hampered its progress as the knowledge economy grew in importance. However, places like New York and Boston, still old industrial centers, had a critical mass of human capital in order to be innovators in the new economy, and thus avoid top down convergence. For regional development policy, the policy approaches needed take two distinct forms. First, industry targeting would appear to be better focused on preparing for the future than chasing the present. Instead of industrial incentives and factory chasing that dominate the news as the tried and true economic development policies, a better approach would be to stop handing out incentives to firms that will be footloose in a few years and focus the efforts towards becoming a leader in the forthcoming industrial cycles. In order to do so, investment in human capital and worker training would appear to be of great importance, as those are the geographic requirements for innovation and industrial location for the early portion of the Product Cycle. Secondly, new industries need to have support structure in place, which is best accomplished through regional investment in transportation connectivity, and business support services. So, through the lens of Regionalism, local governments would be best advised to work together to create a local environment where skilled workers are present, but also have the variety of amenities in place to retain them. Finally, the role of urbanization effects and the positive impact on growth was clear in this dissertation. For growth policy, this lines up well the recognition in Regionalism that a healthy urban core is of importance for the growth of the surrounding communities.

For growth policy, this also indicates that more suburban counties and municipalities in a regional economy should refocus their efforts towards cooperation and supporting the urban core, as opposed to current typical adversarial role between municipal governments, a la Growth Centers. This type of cooperation would likely need to take a role of regional financial support for industrial stabilization, transportation support, but also in areas of school system support, crime prevention, and integrated growth policy. In essence, the municipalities surrounding an urban core are best served by ensuring that the urban core is still a viable location for industrial location, and that is going to take an increase in cooperation and financial commitments.

Directions for Future Research

The primary purpose of this dissertation has been to examine the spatial and scalar effects on beta convergence modeling. I provided an answer to those general questions: spatial effects correct for spatial dependence misspecification, which in turn improves explanatory power, model diagnostic performance, and weakens beta convergence evidence versus non-spatial models. The weakening of convergence evidence is uniform across scales and thus points to a key finding of this dissertation: a reason for incongruent results in convergence tests can come from the handling (or lack thereof) of spatial dependence in the dependent variable. For the other key questions, the size of spatial aggregation was also shown to be a significant potential cause for inconsistent convergence evidence. Larger levels of aggregation tended to have better model fit and explanatory power, but the convergence evidence is strongest at smaller levels of aggregation. However, an interesting result occurs when the conditional and unconditional model results are compared between functional and political levels of aggregation: the functional Economic Areas responded best in terms of model fit and diagnostic performance with the bivariate unconditional model while additional correction variables are needed for the politically aggregated, thus suggesting a different conditional processes occurring at the politically defined geographies. So, depending on the nature of the aggregation unit, differing models, and in turn convergence processes, may be occurring. This result provides a strong evidence about the role scalar effects can play in convergence test result disparity.

Outside of simply answering those questions, this dissertation also set the stage for a line of research comprised of several new convergence papers. These papers fall outside of the standard research continuations dealing with expanding the time period and study area. In this case, those standard expansions would include the convergence process through earlier Kondratieff Wave transitions, and how convergence has occurred internationally, such as including Canada and Mexico in the current time period capturing the implementation of NAFTA. The first paper in this new line revisits the issue of spatial aggregation. Here, although explored at three levels of aggregation, additional levels of aggregation are possible. Future research will be focused on the construction of a new-mid level of aggregation through the use of boundary analysis techniques. The goal, then, is to find the truly functional and independent regions in which the convergence process is occurring, and identify the impact of this independence on model fit and convergence evidence. Additionally, another issue with model specification comes from how income is measured. Although PCPI is a standard measure, additional measures of income can include measures with output such as per capita value added. This can help see if differing measures of regional wealth and investment are uniform in capturing the convergence process. This issue of specification problems arising from measures of income also opens the door for the role that regional price deflators is another area of research. As a whole, the issue with different values of the dollar over space has been ignored in convergence analysis. One avenue of research then is to explore how strong convergence evidence is once regional dollars are converted to regionally constant dollars and also if regional price deflators converge in accordance to income change as well.

Outside of the specification papers, the conditional results also set up a line of research on the endogenous feedback of explanatory variables. The first of these, as was noted in both the conditional and unconditional model, deals with the spillover impacts associated with employment specialization. Looking at the outliers, the regions focused on the higher knowledge service employment tend to be spatial outliers suggesting an inability to spur growth along in their neighboring regions. The research interest here, then, is to investigate why the spillovers in those urban areas where these specializations failed to spill over in contrast to the spillovers that can occur with manufacturing specializations. A secondary area of research also deals with the role of urbanity in development. In theory, both rural and urban forces should have influence on growth, as rural development could be spurred by filtering down of industries (as suggested by Product Life Cycle Theory), and urbanization economies would help development in urban areas (as suggested by the agglomeration literature). However, urbanization appeared to be the more important factor in the model, and thus, the research questions are related as to why it was more important than filtering down, and then to find a better understanding of the role that rural areas play in the more modern economy.

In a more practical, policy orientated arena, the surprising Right to Work results warrant further exploration. More specifically, the Right to Work variable was only significant at smaller levels of aggregation, and the areas under Right to Work legislations displayed faster rates of PCPI growth than those without this legislation. In the examination of Right to Work legislation on growth at the smaller levels of aggregation, the initial results point to Right to Work impacts being considered by firms after a regional location has already been selected. Once that regional location has been selected, if a Right to Work location is available, it will be more attractive, but only after other factors have been considered. The implication, then, is that Right to Work legislation may only attract growth at a local level in a Tiebout (1956) style sorting. This localized sorting based upon state level legislation then presents the opportunity for two papers. The first of these is an investigation on possible border effects of Right to Work legislation. Here, the study would focus on EAs that cross borders between Right to Work and non-Right to Work states and examine firm birth, death, and movement upon Right to Work enactment. The fundamental research question here, then, would question the extent to which RTW legislation is considered in the sorting of firms within a functional Economic Area, and if that consideration is uniform across sectors. The second policy oriented Right to Work paper builds upon the results of both this dissertation research and the firm sorting research. In this research line, the role of firm sorting, Right to Work status, and economic development are tied back to the "new" Regionalism discussed previously.

In the new Regionalism, the support for a regional approach to governance comes from a recognition that functional economies are regional in scope and that greater economic growth can be achieved through the coordination of efforts and resources. This larger scale approach operates in contrast to the more localized approach that suggests municipalities can achieve economic advantage through offering a unique bundle of inputs for firms. At the center of this difference is the issue of scale. The new Regionalism is focused on aggregate growth for the region, which is then assumed to benefit all. In essence it creates a larger pie, while the localism approach tends to focus on how the existing pie is divided. The border EAs and their component counties from this dissertation offer an intriguing study area for an inquiry as to which approach is better for growth. In these functional economies, a sorting variable is imposed at the state level.

The initial dissertation results suggest that firms are sorting based upon that variable, and the initial spin off paper will further explore the extent of that sorting. What is of interest in this additional study is how the local governments responded to that imposed sorting variable, and how those economies performed in the growth model. Specifically, I am interested in identifying the Economic Areas that responded to that imposition with a further localization policy approach, and those functional economies that side-stepped the imposed sorting and took a regional approach to growth. With the EAs classified, growth rates, firm births, firm deaths, and firm movement can be compared. At the EA level, the overall growth rates and convergence modeling approaches can be compared in order to determine if a strong localization approach to economic development produces a slower growth rate in the regional economy as theorized by the new regionalists.

Secondly, this line allows for a comparison of growth rates at the smaller levels of aggregation, where localized sorting policies would be implemented. Here, I am interested in looking the individual counties in the "localized" EAs that captured the fastest growth and comparing them to the counties the "regionalized" EAs. This comparison of growth rate, model performance, and firm health allows for an investigation of a fundamental argument of new regionalism, that greater economic gains can be found through a promotion of the economy as a whole than through localized competition.

A final Right to work extension deals with the growth of income in Right to Work locations. With the significant and positive role in the model, this variable indicates that regions with de facto wage ceilings display faster income growth than those that do not. This warrants further investigation in that the growth in wages is exactly the opposite of what the legislation should ensure, so the spin-off paper should be focused on the role of RTW legislation in income growth, and then if there is a critical value of growth where it stops attracting firms.

A final area of policy related research comes in that are related to the two-tiered economic development structure discussed previously. Here, this paper would be less of an empirical assessment, but rather a discussion of a new approach to economic development policy that incorporates both Regionalist and localist ideals. In this paper, localism would be promoted through the sorting of firms once they have been attracted to a region, but also though the argument that this style of sorting also be done at the regional scale, as regions will be competing with each other to offer a bundle of amenities attractive to firms. Tied back to Regionalism, this case will be made through governments working together to attract a larger pie. As such, this new proposal for economic development may indeed provide a compromise that satisfies both the supporters for Regionalism and the supporters for localism.

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