Geographical Concentration and Economic Growth:

Do Externalities Matter?

Mihai Nica

Jackson State University

155 B Parkhurst Dr.

Jackson, MS 39202

M_nica@hotmail.com

Mihai.P.Nica@jsums.edu

Abstract

Regardless of the reasons leading to its formation, it is widely accepted that geographical concentration of economic activity triggers increases in productivity. However, there are almost no studies that analyze the relationship between geographical concentration and economic growth. Moreover, when looking at the relationship between geographical concentration and productivity, past research almost unanimously modeled the underlying externality based on a scale measure (size) or an index.

Starting from the assumption that the influence of geographical concentration on growth can be best modeled taking in consideration an intensive measure, such as population density, as an indicator of externalities, this study uses a growth accounting framework to assess the effect of geographical concentration on economic growth. It finds population density to be a good candidate for evaluating the externality influence, since a significant portion of the variation in economic growth over U.S. counties and BEA regions is explained by differences in population density.

Introduction

It is generally accepted that geographical concentration of economic activity (GC) influence productivity and that this influence leads to increasing returns. The underlying mechanism that generates increasing returns is however still a matter of debate, and, without an accepted theoretical base, difficult to model. Hence, it is also difficult to empirically assess the extent to which GC explains the large productivity variation observed across regions and countries. The common approach however is to model its effects based on the size of the economy (or an analogous scale factor). A possible alternative, mostly ignored by the literature, is to consider an intensive measure as the main indicator of GC.

One of the few (the first one, as suggested by the authors themselves) papers that pursued this alternate approach was published relatively recent (Ciccone and Hall 1996), but surprisingly with little follow-up in the literature. Ciccone and Hall (CH) show that taking in consideration economic activity density at the county level is instrumental for explaining variations in productivity at the state level. Following their lead, this paper attempts to contribute to the literature by considering population density as an indicator of GC and therefore of the underlying externalities. In addition, its empirical framework focuses on the relationship between GC and economic growth, an approach that allows for evaluating the importance of externalities in this context.

The paper continues by presenting some past findings and suggesting a theoretical framework that relates economic growth to productivity and therefore GC. It then suggests a simple model of endogenous growth (mostly in a growth accounting framework) laying down the motivation for the empirical work. After presenting the data and some results from its exploratory analysis and the empirical estimation of the model, the paper ends with conclusions and suggestions for further research.

Geographic concentration and growth

The process that leads to the geographic concentration of economic activity (GC) is, at least in theory, fairly simple. In the first stage the seed of a future such GC appears due to random events or reasons such as proximity to natural resources and it further expands to form clusters of economic activity[i]. The literature attributes the expansion process to specific effects such as MAR or Jacobs (Glaeser Kallal 1992), or, more generally, to the appearance of generalized external economies (Krugman 1991) or competitive advantages (Porter 1990). And, regardless of the reasons leading to its formation, it is widely accepted that GC trigger increases in productivity, at least in the case of modern urban economies (Becker et. al. 1999).

Moreover, models describing the link between GC and increasing returns predict a circular causation of concentration for (at least) the non-agricultural labor (Krugman 1991), and therefore accelerating growth. While the empirical work did not always support this hypothesis (Jones 1999) the poor results may be the consequence of two main limitations. First, most studies focused on city or metropolitan areas ignoring what happens beyond their borders. Secondly, and maybe more important, they only considered a scale measure such as city (population) or industry (more specifically the employment share of one industry or a Herfindale-type index) size as indicators of agglomeration economies. It is then possible for other specifications to yield better empirical results.

In a relatively recent groundbreaking study, Ciccone and Hall (1996), from now on CH, analyze the influence of externalities on productivity considering economic activity density (and not a size measure) to be the main indicator of their presence. CH model the production function of a certain area as having a constant elasticity of output with respect to employment (production elasticity) and to density (externality elasticity). The product of the two elasticities determines if higher densities lead to increased returns. After aggregation they define a density index that allows for indirect evaluation of the product of the two elasticities[ii]. While not specifically looking at the relationship between externalities and growth, they provide strong evidence that economic activity density influence productivity.

CH also compared the implied density and size (measured as output per county) effects. Their results suggests that density externalities are more important then size externalities, supporting the hypothesis that density may be a more adequate base for quantifying the influence of GC. CH conclude that associating externalities with other measures of concentration may not be adequate. Another interesting observation is that their estimation methodology rests in part on the assumption that past patterns of agglomeration at a specific location have a significant influence on present productivity. As illustrated further, this assumption appears to be sound (albeit not necessarily supporting their methodology).

But, although the paper opens a very interesting line of research, there seem to be little interest for it. The only directly related study looks at the influence of metropolitan density on productivity from a similar perspective (Harris and Ioannides 2000). Using the same methodology (except for the estimation technique, since Harris and Ioannides used OLS, while CH used a nonlinear instrumental variables estimator), they introduced population size as an indicator of Jacobs externalities, and circumvented the use of the density index. Their results parallel CH's ones, suggesting again that doubling employment density leads to an increase in productivity of about six percent.

But while the link between GC and increasing returns is acknowledged both theoretically and empirically, it is ignored by the body of literature that investigates exactly the influence of increasing/decreasing returns on economies-economic growth. Economic growth models express the dynamics of percapita income (or a more specific measure of productivity) as being dependent on one or several local factors. The main explanatory variable is usually percapita income (or a related variable) at the beginning of the period, whose coefficient is expected to be negative and statistically significant. Indeed, if economies exhibit decreasing returns, their growth slows while they become richer, and therefore, poorer economies grow faster, thus convergence occurs.

However, if an area with a rich economy exhibits diminishing returns, but GC is present and leads to increasing returns, their combined effect could lead to having richer economies growing faster. Thus, taking in consideration the effect GC has on productivity (and economic growth) could bring a complementary insight. Moreover, since GC is present within very homogenous economies, it should be accounted for even in an absolute convergence framework. Indeed, people are less mobile then any of the other resources and if one accepts that GC influences productivity, it must be that it also influences the geographical distribution of economic growth. But in order to analyze economic growth from such a perspective, it is necessary to formally model the process.

The Model

The theoretical approach of this paper is designed to add insight to the literature on economic growth already in place, by analyzing the influence of GC without focusing on a particular theory. The model developed is then further specified in a Solow-Swan type framework to allow for empirical estimation, but any other model may be taken into account. The reader interested in further assessing the implications for a certain type of economic growth model may consult the very rich underlying literature (e.g. Ramsey 1928, Solow 1956, Swan 1956, or for a discussion of alternatives BSM 2004)

The main assumption of the model is that the economies under scrutiny are operating at full employment, and are homogenous enough (except for GC) to apply an absolute convergence framework. Thus the differences between the regions of interest appear only due to initial percapita income and GC (any other possible sources of heterogeneity such as ideas, technology, and the like are disregarded, equivalently to either considering they diffuse instantaneously across space or their influence is accounted for through GC). In addition, each location's area is constant over time, hence $\frac{dA}{dt} = 0$, and, as is the norm in the growth literature, population grows at a constant rate $L = L_0 e^{gt}$ (the suffix *i* which usually indicates different areas is ignored to simplify the equations).

Starting from the classical growth theory and considering a production function

$$Y = F(K, L) \tag{1}$$

where, as usual, *K* is capital and *L* is labor, the effect of GC can be expressed by a multiplicative term:

$$Y = d(\delta, t)F(K, L) \tag{2}$$

where δ stands for density. It is easy to see that all properties of the classical production function are maintained. Accordingly, since only *d* depends on density, one may interpret the production function for *d*=1 as the underlying production function for economies with constant density across space. In intensive form, the production function becomes:

$$y = d(\delta, t) f(k) \tag{3}$$

A reasonable form for *d* would be compatible with a Cobb-Douglas specification. Consequently, we have:

$$d = \delta^{\gamma} \tag{4}$$

Considering the saving rate constant across the economy at any given point in time, there will be excess capital in more dense regions. In order to equalize the percapita productive capital, there are two opposed movements in the economy, with capital flowing from the richer towards the poorer regions and with workers migrating in the opposite direction.

Dynamics with no labor migration

With no labor migration and constant areas, density in each location grows by the same growth rule as population (working force):

$$\delta = \frac{L}{A} = \frac{L_0 e^{gt}}{A} = \delta_0 e^{gt} \tag{5}$$

Since labor is spatially fixed and only capital flows freely we have:

$$y = \delta^{\gamma} f(k) \tag{6}$$

and taking logs:

$$\ln y = \gamma g t + \gamma \ln \delta_0 + \ln f(k) \tag{7}$$

which, after subtracting income at time t_0=0 from both sides and arranging terms becomes:

$$\frac{1}{T}(\ln y - \ln y_0) = \gamma g + \frac{1}{T}[\ln f(k) - \ln f_0(k)] \tag{8}$$

This equation shows that, with no migration and full employment, the annual percapita income growth in a certain area is higher or lower (depending on the sign of the population growth in the area) than the one predicted without taking in consideration GC by the product between density elasticity and the population growth rate. If GC has no influence on income, the equation reduces to the familiar growth equation as expressed in the literature.

Dynamics with labor migration

When labor is mobile, the change in density has two components, from local growth and from in or out-migration. Expressing again the influence of migration on density as a multiplicative term:

$$\delta^* = \delta\ M \tag{9}$$

where *M* reflects the increase (or decrease) of density due to migration in each location, the production function becomes:

$$y = (\delta\ M)^{\gamma} f(k) \tag{10}$$

In the growth literature the effect of growth augmenting variables such as technology, human capital, and more generally, spillovers, are analyzed by incorporating them in a neoclassical growth model (Barro and Sala-i-Martin 2004). In particular, the treatment of migration is somewhat secondary, by incorporating its effects in the underlying effective depreciation rate and therefore analyzing them from a capital-augmenting perspective. Specifying the migration function as a positive relationship between the migration rate and the per capita effective labor capital or the wage rates in different basic models (e.g. Solow-Swan, Ramsey), Barro and SM (2004) conclude that the inclusion of migration in such models leads to a minor increase in the convergence speed.

However, migration between regions within homogeneous economies cannot be analyzed within such a framework because the difference between the migrants and locals' capital is much smaller. Furthermore, if there are significant externalities associated with GC, it seems logical to expect that the area experiencing out-migration would experience a slower economic growth, while the area experiencing in-migration would grow faster. Therefore, such models describe only the influence of migration on economic growth from a narrow perspective, without taking in consideration the possible externalities that appear due to concentration of migrants in certain areas.

On the other side, the circular reasoning of concentration assumes that workers are attracted and are migrating towards the area where GC appears, which then becomes even more attractive and the cycle repeats. Models such as those developed by Krugman (1991, 1993) predict concentration of labor, but they are less helpful when it comes to assessing the dynamics of the influence of migration on productivity. Since there is no clear preference towards a certain specification of the migration process in this case, a possible form is as follows:

$$M_t = M_0 \delta^{mt} \tag{11}$$

which expresses migration at a certain point in time as a function of density at that point, a specification compatible with the highly debated Gilbrat law. Accordingly:

$$\dot{M} = m \ln \delta \tag{12}$$

(where a dot above the variable signifies its growth) and integrating:

$$M = e^{m(t \ln \delta_0 + \frac{gt^2}{2})} \tag{13}$$

therefore income becomes:

$$y = \delta^{\gamma} e^{m(t \ln \delta_0 + \frac{gt^2}{2})\gamma} f(k) \tag{14}$$

The outcome of this specification is the identification of a speed and acceleration of *M* growth, which in turn gives a speed and acceleration of density hence productivity growth. While theoretically this is expected, it is interesting to see that this specification actually spells out their form. However, their influence may be somewhat small, since they depend on the γg, $\gamma m \ln \delta_0$ and γmg terms respectively. Taking logarithms and expressing percapita income growth as a difference of logarithms:

$$\ln y_T - \ln y_0 = \gamma gT + \gamma m \ln \delta_0 T + \frac{\gamma mgT^2}{2} + \ln[f(k_T) - \ln f(k_0)] \qquad (15)$$

and the annualized growth between two periods (considering, as before, $t_0 = 0$) can be expressed as:

$$\frac{1}{T}(\ln y_T - \ln y_0) = \gamma g + \gamma mg\frac{T}{2} + \gamma m \ln \delta_0 + \frac{1}{T}\ln[f(k_{t+T}) - \ln f(k_t)] \qquad (16)$$

Finally, assuming *f(k)* to be a Cobb-Douglas production function with technology, the equation becomes (Mankiw Romer and Weil 1992, BSM 2004):

$$\frac{1}{T}(\ln y_T - \ln y_0) = g\gamma + \gamma gm\frac{T}{2} + x + \frac{1-e^{-\beta t}}{T}\ln y^* + \gamma m \ln \delta_0 - \frac{1-e^{-\beta t}}{T}\ln y_0 \quad (17)$$

where x represents the technology rate of growth and y^* the common steady state. Following the approach common in the growth literature, one can estimate both equations (8) and (17) after collapsing the first terms into a constant. The two growth equations suggest that, besides the beginning of the period income, the beginning of the period density also has an explanatory role in the evolution of economic growth at a particular location.

Data and Estimation

This section begins with some exploratory data analysis (EDA) and, as it becomes common in regional science and not only, with some exploratory spatial data analysis

(ESDA). Like its classical counterpart-EDA, ESDA allows for visualization of possible spatial patterns in the data, as well as identification of spatial relationships (Anselin 1995b, TerraSeer 2002). Based on the interpretation of the EDA and ESDA several nested models are estimated. After the results of the estimations are presented and discussed, the section ends with a description of the main results and the discussion of their importance and relevance.

Data

The data is compiled from the 2002 Regional Economic Information System (REIS) CD-Rom, which contains several time series for the 1969 – 2001 interval (REIS 2002). Amongst other series, the CD-Rom contains information at the county level for personal income by major source and for population. The dataset was matched with a shapefile containing the relevant geographical information (including areas for each county) using the FIPS field. After eliminating the counties with missing data the dataset has 3030 observations, therefore only less then three percent of the universe was dropped from the analysis. The variables of interest are the logarithm of the real percapita 1969 and 2001 income (LRPI1969 and LRPI2001), and the logarithm of the 1969 population density (LD1969).

The largest counties with incomplete or null data are situated in Arizona (La Paz), Florida (Dade), New Mexico (Cibola), and Montana (Yellowstone National Park). The state with the highest number of counties with missing data is Virginia, where 55 counties with an average area of 220.84 square miles are missing. However, the areas are small and mostly contained within larger counties, and therefore their influence negligible. Two counties from Wisconsin (Menominee and Shawano) are also missing. A different approach to handle missing data would have been to estimate it by some methodology, but, due to the small percentage of dropped counties, the benefits would have not overweight the possible negative effects such as the introduction of spatial correlation in the data.

Table 1 about here.

Table 1 reports some descriptive statistics for 1969 and 2001, corresponding to the 3030 counties sample. Maybe the most interesting (although well known) fact is the counties' aerial diversity. The largest county is San Bernardino (CA) with about 20,175 square miles while the smallest is Mohave (AZ) with only 4.6 squared miles. It is also interesting to see that, for the period of the study, the annual real percapita income growth (AVG_GR) varies from a decrease of about 2.3 percent (Sherman, OR) to an increase of over 8 percent (Loving, TX). As expected, the lowest coefficient of variation corresponds to the logarithm of 1969 population density (LD1969).

Figure 1 about here

Figure 1 shows plots with fitted regression lines for each pair of variables. It suggests relatively strong relationships between variables, with Loving (TX) as the most significant outlier. Other noticeable outliers are Grant (NE), Sherman (OR), and New York (NY). The logarithm of real percapita income (LRPI) plot suggests a lower fit for the areas with high initial percapita income, while the LD plot suggests a lower fit for areas with low average density. The former could be explained by the fact that counties with initial high income were also counties with high initial densities. The later case could be explained by the way density is computed. Indeed, for many counties there are large differences between the nominal area and the dwelling area, therefore the differences between nominal density and real density will be significant. And this difference is expected to be high exactly where the average density is low (large counties with small inhabited areas).

Figure 2 about here

An interesting snapshot of the relationships between real percapita income growth and log of initial percapita income and of density for each of the eight BEA regions is shown in Figure 2. It can be seen here that, at least for LRPI, the relationships at the region level are not as straightforward as they seem to be at the aggregate level. The most interesting cases are regions 1 and 2, where there seems to be a positive relationship between AVG_GR and LRPI1969, and region 8, where the relationship seems to be very weak, if any. However, the figure reveals what seems to be a more stable relationship between AVG_GR and LD1969, but further statistical inquiry will bring more light upon this issue.

Figure 3 about here

Yet another insight on the data and underlying phenomena may be gained from a time-series perspective; Figure 3 presents notched box plots corresponding to each year for both independent variables. As expected, LRPI exhibits an upward trend and a far from normal distribution. The two extremes correspond to New York (NY) and Loup (NE), both at some distance from the “main block” (neighboring counties are Pitkin, CO for New York and Blaine, NE, for Loup). Interestingly, both counties separated from the main group at about the same time, somewhere around 1986 and never converged back. And, for the interval under study at least, they were always at the extremities.

In the case of LD, the trend is less apparent, although it appears to be also upward. The two extremes correspond to New York (NY) and Loving (TX), both amongst the counties with the highest percapita income in the US. While New York is less of an outlier in this paper's perspective, Loving represents an interesting case which however does not necessary mean anything else than what it is, an outlier. Probably the most important conclusion arising from the above exploratory data analysis is that, when it comes to convergence, not all regions behave similarly, but that, for this data at least, the positive relationship between density and economic growth seems at least as stable as the widely acknowledged β convergence.

Figure 4 about here

Since the working hypothesis is based on the assumption that the creation of GC is explained by externalities, and since such externalities would lead to interactions between neighboring economies, the possible spatial dependence between regions should be addressed or at least investigated. The need for such an approach was highlighted by several scholars who pleaded for shifting the focus of research from treating areas of interest as "islands" to taking in consideration the spatial dimension of the phenomena (Quah 1996b). Fortunately, relatively new methodologies that take in account the possible spatial dependence begun to play an increasingly explicit role in economics and econometrics and are readily available (Anselin 2003). Furthermore, the explosion of GIS software and data made this type of investigation efficient and relatively easy.

Figure 4 reveals the quantile map of real percapita income growth for the period under study. The counties with the highest growth (darkest color) are situated in the East South Central, South Atlantic and West North Central divisions, while the counties with the slowest growth are situated mainly in the West, and Midwest as well as East North Central and Middle Atlantic divisions (most of the white spots within Virginia indicate counties where no data was available). While the map suggests the existence of spatial clusters, the statistical significance of the observed pattern can only be assessed empirically.

The framework for assessing the significance of the spatial autocorrelation in a spatial dataset is somewhat similar to assessing autocorrelation in time series data. One of the most common statistics for spatial dependence is Moran's *I* statistics which aims at identifying departures from random spatial distributions (Moran 1948). The formula is:

$$I_t = \left(\frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \right) \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} x_{i,t} x_{j,t}}{\sum_{i=1}^{n} \sum_{j=1}^{n} x_{i,t} x_{j,t}}$$

where *n* is the number of areas and *x* represents the value of the measure of interest in a certain area. The statistics is a weighted correlation coefficient where the weights reflect geographic proximity, and, as in the case of autocorrelation, if the statistics is significant its sign represents the nature of the spatial dependence. Therefore a significant negative value indicates negative spatial correlation. However Moran's *I* does not indicate where the spatial correlation occurs, but merely if it is statistically significant for the whole area under scrutiny.

Anselin (1995a) introduced a modified Moran statistic aimed at identifying local spatial clusters, called Local Indicator of Spatial Association (LISA). The formula is:

$$I = \left(\frac{x_i}{\sum_{i=1}^{n} x_{i,t}^2} \right) \sum_{j=1}^{n} w_{i,j} x_{i,t}$$

and measures local similarity (dissimilarity). A large positive value of *I* signals a local set of similar values in the neighborhood (around region *i*) while a large negative value indicates dissimilar values. Therefore, while Moran's *I* indicate the presence or absence of spatial dependence in the data, the LISA statistic indicates the actual location of these dependencies. Both statistics are becoming widely used in the literature.

Figure 5 about here

The Moran's *I* statistics for the 3030 counties is 0.4356, which after 999 permutations is significant (p = 0.0010). The LISA statistics ranges from –11.43 (indicating strong negative spatial correlation) to 15.82 (indicating strong positive spatial correlation). The quantile map of the LISA statistics is shown in Figure 5, and suggests that the largest cluster of counties with strong positive spatial correlation is in the West, while several other clusters exist. However the spatial pattern is not completely clear without assessing its statistical significance. Figure 6 shows the *p*-values for the LISA statistics as obtained after 999 Monte Carlo randomizations. The spatial clusters are even clearer, suggesting that they are made up mostly of counties with positive spatial correlation.

Comparing the maps it is interesting to observe that, while the first one gives an idea of the areas with similar growth, the LISA maps gives a picture of the relationship between neighboring regions. Due to the apparent strong spatial patterns, tests for significant spatial dependence, model misspecification and heterogeneity will also be performed. Should the tests reveal the need for a specification that takes in consideration the spatial association, a spatial model will be considered. The next section presents results of the empirical estimation of several nested models.

Estimation

Baumol (1986) opened a highly debated line of research suggesting that economies with lower percapita income tend to grow faster, and that the convergence speed is somewhere around two percent per year. His empirical study led to a very reach literature aimed at finding the best methodology for evaluating the speed of convergence, but no one methodology gained more recognition over the others (a comprehensive literature review and discussion of this research appears in Temple 1999 and BSM 2004). According to the mainstream growth literature however, there are several issues that have to be considered when estimating an economic growth model.

First, when data cover a relatively short time span, a panel approach (first proposed by Islam 1995) might be less adequate due to the inherent short-term business cycle related fluctuations in productivity (BSM 2004). Therefore the common approach is to work with the average of percapita income growth for the period under study. Unfortunately such an approach cannot reveal the intradistribution dynamics, falling short of revealing if the distribution is unimodal, bimodal or even multimodal (Quah 1996a). Second, the question of homogeneity of the units of analysis also arises. In order to estimate an equation such as (17) one has to account for possible biases in data due to different standards and imperfect conversions (Dowrick and Nguyen 1989, Dowrick and Quiggin 1997). However, if the units of study are within the same country the above issues are less stringent and absolute convergence is usually assumed.

Thirdly, as suggested above, the spatial interaction between variables may be also taken into account in the estimation. The decision between the possible specifications relies as usual on theory and econometric tests, and several recent papers describe the specification selection process (Anselin 2002). Without going into too much detail, a model of the form (in matrix specification):

$$y = X\beta + \varepsilon \tag{18}$$

which does not take in consideration the possible influence of the neighboring economies may be amended to reflect such interactions in several ways. Two of the most used spatial models specifications are the spatial lag and spatial error models. The spatial lag model is expressed as:

$$y = \rho W y + X\beta + \varepsilon \qquad (19)$$

where ρ is a spatial autoregressive coefficient and W represents a set of weights (a weight matrix) associated to each area where the variables are measured. The weight matrix consists of positive elements $w_{ij} \neq 0$ for neighbors and $w_{ij} = 0$ for areas which are not in the vicinity of each other (Anselin 2002). The spatial error model is taking in consideration that the errors are non-spherical. The implied specification is:

$$y = X\beta + \varepsilon \text{ with } \varepsilon = \lambda W \varepsilon + u \qquad (20)$$

Ignoring the presence of spatial correlation has the same effect as ignoring autocorrelation in the case of time series, that is, OLS estimation would be unbiased but no longer efficient (Anselin 1999). While in practice deciding between the two specifications could be difficult, one has to remember that their interpretation is also different. A spatial lag model is appropriate when the focus is on estimating the influence of the neighboring observations on the dependent variable. A spatial error model only attempts to control for possible influence of the spatial autocorrelation (Anselin 1999).

Since the EDA suggests possible different relationships between variables corresponding to BEA regions, it may be also interesting to analyze each region separately. Table 2 reveals the results for the classical growth-initial income, the growth-initial density, and the combined model regression corresponding to each region. The first interesting observation is that the classical convergence test fails for three regions. Indeed, for region 1 and 2 the initial income coefficient is statistically significant but positive, while for region 8 it is not significant. Moreover, neither the adjusted R^2 nor the

AIC indicates the classical growth initial income regression as the best specification amongst the three alternatives.

On the other side, for the growth-initial density model, the initial density coefficient is not significant for two regions (3 and 5) but it is always positive, and furthermore, it is as expected for all regions in the combined model. Indeed, with the exception of region 1, the best specification seems to be the combined model, as indicated by both the adjusted R^2 and AIC. The initial income coefficient for region 2 remains positive for the combined model, while for regions 3 to 6 varies from -0.0105 to –0.0168. For the chosen models the initial density coefficient varies from 0.0005 to 0.0021, suggesting a positive relationship throughout the regions. The relationship is significant even for those regions where for the growth-initial density model it was not.

Since due to the modifiable areal unit problem (Heywood 1988), and not only, one expects that these results could be different if the analysis unit is the whole country, tests of convergence were also run for the entire sample, but this time only the combined model was considered. In order to decide the model specification a simple OLS regression and a battery of tests were run (some of the results are showed in Table 3). The Jarque-Bera test has a value of 16,083.98, which is highly significant for two degrees of freedom, suggesting nonspherical errors. Both White test (with a value of 360.3084 and five degrees of freedom) and the Koenker-Basset test (with a value of 11.1303 and two degrees of freedom) are also significant, suggesting heteroskedasticity.

The tests also suggest a significant spatial dependence in the data indicating the spatial-error model as the best specification, since the Robust LM test for the spatial lag model is not significant, p = .6767 (Anselin 1995b). All the other tests for spatial dependence (Moran’s *I*, Lagrange multiplier-LM, and Robust LM for errors) are significant to at least seven digits. The results for the maximum likelihood evaluation of the spatial error model are also shown in Table 3. Although they do not show a significant difference between the two models (the coefficients differ only marginally while remaining statistically significant), they suggest a relatively good fit and a strong spatial dependence (the Likelihood ratio test is highly significant). Finally, a classical OLS and a spatial error model that allows for distinct intercepts and for distinct coefficients, having BEA regions as factors, were also run. The results were similar, with negligible differences in the intercepts and coefficients between each of the eight regions, and therefore are not shown here. Heteroscedasticity corrected estimations did not change the results either (although lowered the *t* statistic for the variables), and therefore are not reported.

Regarding the so-called general convergence test, it seems safe to conclude that there are rather small differences between the OLS and the spatial error specifications[iii]. For the spatial model both Akaike and Schwartz criteria decrease slightly while R^2 increases, suggesting a better specification, but the change in the LRPI coefficient is fairly small (less than five percent) and there is no change for the LD1969 coefficient. Working with state level data for the 1929 – 1994 period, Rey and Montouri (1999) reported convergence rates of .019 for the simple OLS regression and .018 for the spatial error model, both highly statistically significant. Using a nonlinear estimation and working with state level data for the 1880 – 2000 period, Barro and SM (2004) found convergence rates of .0172, again highly significant. In both papers the coefficients tend to be much smaller for shorter time intervals, and so does R^2.

A first observation regarding the influence of GC on growth is that its elasticity is about one measurement order lower than percapita income elasticity. With log density in

1969 varying from a low of – 1.8154 to a high of 11.1230, its influence is significant but does not reverse the fact that counties which had lower income in 1969 experience higher rates of growth. Indeed, assuming a county had the highest initial density and the highest initial income, its growth rate would still be behind the county that had the highest initial density and the lowest initial income. The results also suggest economic growth even for the counties with the lowest initial densities. Indeed, for the lowest possible initial density and the highest possible initial income an annual growth of 0.00048 would still occur.

The highest growth due to the density effect can be of about 0.0167, which compared with the actual highest growth of .0841 show a possible influence of about 20 percent. Thus the initial hypothesis holds, and there are cases when counties with higher initial percapita income are growing faster then counties with lower initial percapita income if their initial density was higher. Furthermore since density growth occurs exogenously in this model, it influences economic growth accordingly. The implied value of the term γm is .0015 corresponding to a rate of percapita income growth (due to migration) of about .0051 and to an acceleration of .00003, which are relatively low and may explain the difficulty of assessing them empirically. The implied convergence speed is .0142, which, as expected, is lower than the one suggested by previous studies.

Overall it may be concluded that GC plays a significant role in the convergence process. However it does not reverse it, at least in the short run. As discussed above, even if there are regions where divergence occurs at least partially due to density, the overall test shows that for the time period under study density cannot offset the influence of the initial percapita income. This finding is consistent with the relatively slow change in density over the period as revealed in Table 1 and Figure 2. While a more precise measure of density would improve the fit of the models, the overall conclusions would however still hold.

Conclusions

A few interesting conclusions may be drawn from this analysis. First, density seems to play a significant role in explaining growth, and amending the classical convergence tests to include its effects seems worthwhile. Indeed, its inclusion in the model leads to a better specification, and, at least for the data under scrutiny, the positive relationship between percapita income growth and initial density seems robust. Second, for the overall convergence test density does not offset the influence of initial percapita income. The combined specification however seems to allow for more precise estimation of the convergence coefficient.

Third, there are almost negligible differences between the OLS estimation and the spatial error model estimations. However the spatial error model provides a better fit and more insight could lead to interesting insights. Moreover, it may be the case that for smaller areal units a spatial model would reveal relevant facts (especially if the LISA statistics shows a large bias toward a positive or a negative spatial correlation in the data). For example considering a region that has only a large metropolitan area with strong growth, a strong positive spatial correlation may appear and then the results obtained from a spatial model could differ significantly.

There are several issues raised in this paper that might prove good leads for further research. Taking in account the errors introduced when calculating density, a study at the zip code level could allow for more precise estimation (the density variable would be measured more precise). Also, the use of complimentary methodologies that allow for analysis of the intradistributional dynamics would bring further insights into the growth process and the role played by spatial externalities. Finally, a focused ESDA could bring even more insight in the role that spatial dependencies play in the process for regions where the LISA statistics is strongly biased, and the degree to which specifying the spatial dependence leads to different results in this specific case.

Bibliography

Anselin, Luc. 1995a. Local indicators of spatial association-LISA. *Geographical Analysis*, 27: 93-115.

___________. 1995b SpaceStat, a software program for the analysis of spatial data, version 1.80. Regional Research Institute, West Virginia University, Morgantown, WV.

___________. 1999. Spatial Econometrics. Bruton Center, School of Social Sciences, University of Texas at Dallas.

___________. 2002. Under the Hood: Issues in the specification and Interpretation of Spatial Regression Models. *Agricultural Economics*, 27 (3): 247-267. Nov.

__________. 2003. Spatial Externalities. *International Regional Science Review*, 26: 147-152, Apr.

Barro, Robert J. Xavier Sala-I-Martin. 2004. Economic Growth. Massachusetts: MIT Press.

Baumol, William J. 1986. Productivity growth, Convergence, and Welfare: What the Long-Run Data Show. *The American Economic Review*, 76 (5): 1072-1085.

Becker, Gary S., Edward L. Glaeser and Kevin M. Murphy. 1999. Population and economic growth. *The American Economic Review*, 89 (2): 145-149.

Ciccone, Antonio and Robert E. Hall. 1996. Productivity and the Density of Economic Activity. *The American Economic Review*, 86 (1), 54-70.

Dowrick, Steve & Nguyen, Duc-Tho, 1989. "OECD Comparative Economic Growth 1950-85: Catch-Up and Convergence," *American Economic Review*, 79(5): 1010-1030, December.

Dowrick, Steve & Quiggin, John, 1997. "True Measures of GDP and Convergence," *American Economic Review* vol. 87(1): 41-64, March.

Ellison, Glenn & Glaeser, Edward L, 1997. "Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach," *Journal of Political Economy*, University of Chicago Press, 105 (5): 889-927, October.

Glaeser, Edward L. and Kallal, Heidi D. 1992. Growth in Cities. *Journal of Political Economy* 100 (6): 1126-1153.

Harris, Timothy F. and Ioannides, Yannis M. 2000. Productivity and Metropolitan Density. Unpublished manuscript, Department of Economics, Tufts University.

Heywood 1998 Introduction to Geographical Information Systems. New York: Addison Wesley Longman.

Islam, Nazrul. 1995. Growth Empirics: A Panel Data Approach. *The Quarterly Journal of Economics*, 110 (4): 1127-1170.

Jones, Charles. I. 1999. Growth: With or Without Scale Effects? *The American Economic Review*, 89 (2): 139-144.

Krugman, Paul. 1991. Increasing returns and Economic Geography. *The Journal of Political Economy*, 99 (3): 483-499.

Krugman, Paul. 1993. Geography and Trade. Cambridge, MA: MIT Press.

Mankiw, N. Gregory, David Romer and David N. Weil. 1992. A Contribution to the Empirics of Economic Growth. *Quarterly Journal of Economics*, 107: 407-437. May.

Moran, P. 1948. The Interpretation of Statistical Maps. *Journal of the Royal Statistical Society*, B 10, 24351.

Porter, Michael R. The Competitive Advantage of Nations. New York: Free Press 1990.

Quah, Danny. 1996a. Twin Peaks: Growth and Convergence in Models of Distribution Dynamics. *European Economic Review*, 40, 1353-1375.

_____________. 1996b. Regional Convergence Clusters Across Europe. *European Economic Review*, 40: 951-958.

Ramsey, Frank. 1928. A Mathematical Theory of Saving. *Economic Journal*, 106 1045-1055. July.

Bureau of Economic Analysis. 2003. Regional Economic Information System (REIS) CD–ROM 1969–2002.

Rey, Sergio J. and Montouri, Brett D. 1999. US Regional Income Convergence: A Spatial Econometric Perspective. *Regional Studies* 33 (2): 143 – 156.

Solow, Robert M. 1956. A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*. 70 (1): 65-94.

Swan, Trevor W. 1956. "Economic Growth and Capital Accumulation." *Economic Record*. 32(63): 327-368.

Temple, Jonathan. 1999. The New Growth Evidence. *Journal of Economic Literature*, 37 (1): 112-156.

TerraSeer. 2002. ClusterSeer: Software for Identifying Event Clusters. TerraSeer, Inc.

Table 1. Descriptive statistics.

Variable	Mean	Median	Min.	Max.	S.D.	C.V.	Skewness	Kurtosis
AREA	994.6600	639.7000	44.7440	20285.0000	1345.8000	1.3530	6.1089	55.8440
AVG_GR	0.0203	0.0205	-0.0231	0.0841	0.0058	0.2854	-0.1513	7.3001
LRPI1969	9.3575	9.3733	8.3636	10.3470	0.2459	0.0263	-0.2516	0.3330
LD1969	3.4184	3.4430	-1.8154	11.1230	1.5212	0.4450	0.1456	1.2287
LRPI2001	10.0060	9.9974	8.7178	11.4200	0.2271	0.0227	0.4611	2.5233
LD2001	3.6866	3.7207	-2.2985	11.1270	1.6194	0.4393	-0.0142	0.6018

AREA – Area for each county as of 2000.
AVG_GR - Average growth; represents the annualized real percapita income growth corresponding to the 1969 – 2001 period.

Table 2. Regional OLS estimation.

Region	Counties	Intercept		LRPI1969		LD1969		R	Adj. R	F		AIC	BP	
		Coef.	t stat.	Coef.	t stat.	Coef.	t stat.			Value	p. value		Value	p. value
		-0.0277	-1.4740	0.0053	2.6810	-	-	0.0995	0.0093	7.1860	0.0093	-593.20	0.1615	0.6878
1	67	0.0193	18.6040	-	-	0.0007	3.4060	0.1514	0.1384	11.6000	0.0011	-597.18	1.1944	0.2744
		0.0107	0.4020	0.0009	0.3260	0.0006	2.0070	0.1529	0.1264	5.7740	0.0050	-595.29	2.9494	0.2311
		-0.0528	-3.3750	0.0076	4.6590	-	-	0.1121	0.1069	21.7100	0.0000	-1429.97	1.9262	0.1652
2	174	0.0154	14.4600	-	-	0.0009	4.6330	0.1109	0.1058	21.4600	0.0000	-1429.75	0.9141	0.3390
		-0.0251	-1.1340	0.0044	1.8310	0.0005	1.7710	0.1280	0.1178	12.5600	0.0000	-1431.13	6.5962	0.0370
		0.0649	6.1490	-0.0049	-4.4500	-	-	0.0439	0.0417	19.8000	0.0000	-3625.49	6.9506	0.0084
3	433	0.0173	24.9700	-	-	0.0002	0.0002	0.0022	-0.0001	0.9475	0.3309	-3606.99	11.3440	0.0008
		0.1120	8.4550	-0.0104	-7.1580	0.0011	5.5770	0.1084	0.1043	26.1500	0.0000	-3653.73	13.3836	0.0012
		0.1260	12.2700	-0.0114	-10.4000	-	-	0.1495	0.1481	108.2000	0.0000	-4813.42	1.0334	0.3094
4	618	0.0159	30.4010	-	-	0.0012	6.7370	0.0686	0.0671	45.3800	0.0000	-4757.31	41.8665	0.0000
		0.1540	16.0200	-0.0149	-14.3800	0.0018	11.6400	0.3029	0.3007	133.6000	0.0000	-4934.40	40.0103	0.0000
		0.1020	18.4300	-0.0085	-14.1700	-	-	0.1681	0.1673	200.9000	0.0000	-8130.43	12.5931	0.0004
5	996	0.0242	38.8930	-	-	-0.0002	-1.0640	0.0011	0.0001	1.1330	0.2875	-7948.26	23.3821	0.0000
		0.1328	21.3230	-0.0126	-17.5030	0.0016	9.4430	0.2366	0.2351	153.9000	0.0000	-8214.08	51.5368	0.0000
		0.1675	14.7500	-0.0159	-13.0500	-	-	0.3123	0.3105	170.3000	0.0000	-2824.42	8.4021	0.0037
6	377	0.0168	22.4720	-	-	0.0010	3.8560	0.0381	0.0356	14.8700	0.0001	-2697.93	16.1996	0.0001
		0.1725	15.9700	-0.0168	-14.4400	0.0013	6.5100	0.3823	0.3790	115.7000	0.0000	-2862.89	21.8443	0.0000
		0.1104	5.4080	-0.0098	-4.5330	-	-	0.0880	0.0837	20.5500	0.0000	-1569.14	24.4827	0.0000
7	215	0.0159	25.6690	-	-	0.0013	4.4430	0.0848	0.0805	19.7400	0.0000	-1568.39	9.8268	0.0017
		0.1117	5.7550	-0.0102	-4.9380	0.0014	4.8540	0.1792	0.1715	23.1500	0.0000	-1589.80	14.6950	0.0006
		0.0657	1.8380	-0.0053	-1.4250	-	-	0.0135	0.0069	2.0300	0.1564	-1055.57	17.0902	0.0000
8	150	0.0092	10.7550	-	-	0.0019	7.9410	0.2988	0.2940	63.0600	0.0000	-1106.76	2.3997	0.1214
		0.1102	3.7290	-0.0105	-3.4190	0.0021	8.7320	0.3504	0.3416	39.6500	0.0000	-1116.24	7.8407	0.0198

AIC represents the Akaike information criterion.
BP represents the Breusch-Pagan test for heteroscedasticity.
Region represents the eight BEA – defined regions.

Table 3. OLS and ML estimation.

Dependent variables	OLS		Spatial error model	
	Value	t-statistic	Value	z-statistic
Constant	0.1414	43.6715	0.1363	32.7855
LRPI1969	-0.0135	-38.4933	-0.0129	-28.7398
LD1969	0.0015	26.4656	0.0015	20.4453
Lambda	-	-	0.4737	21.3754
R-squared	0.3708		0.4760	
Adj. R-squared	0.3703		-	
F-statistic	891.7470	0.0000	-	-
Akaike information criterion	-24,020.30		-24,432.00	
Schwartz information criterion	-24,002.30		-24,414.00	
Breusch-Pagan heteroskedasticity test	73.5395	0.0000	57.4110	0.0000
Robust LM (lag)	0.1739	0.6767	-	-
Likelihood ratio test	-	-	411.7444	0.0000

Lambda represents the spatially lagged error.

Figure 1. Plots with fitted regression lines.

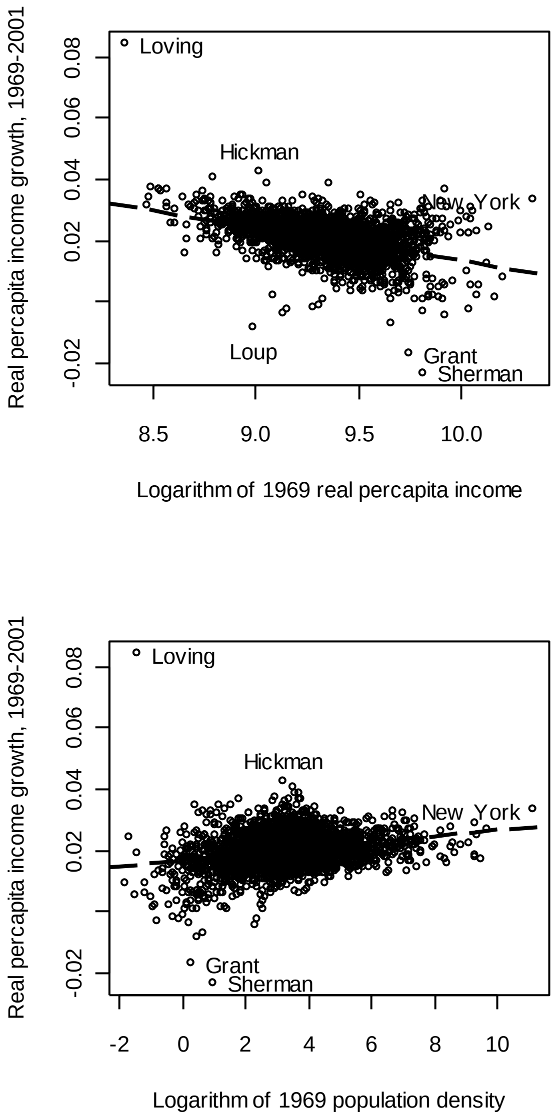
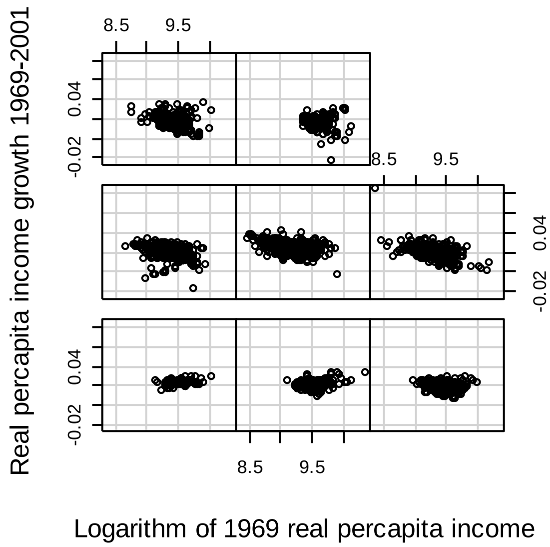


Figure 2. Coplots corresponding to BEA – defined regions.



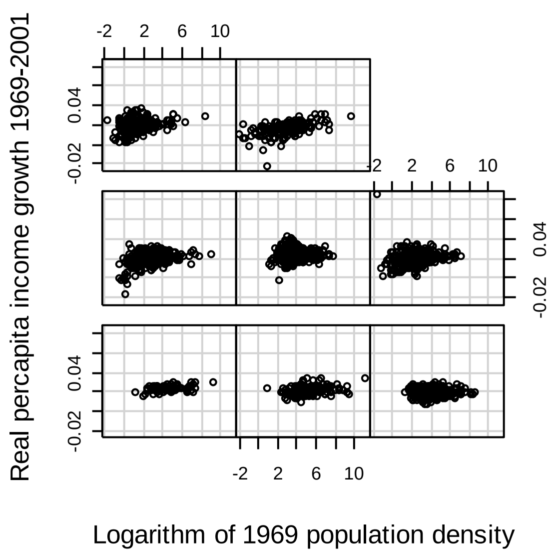
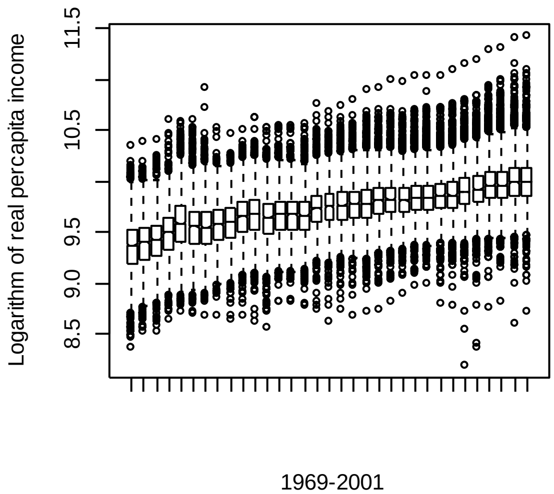


Figure 3. Notched box-plots, LRPI and LD.



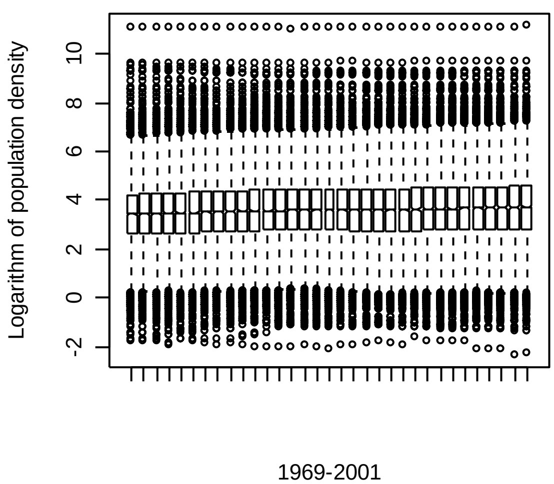


Figure 4. Quantile map of real percapita income growth, 1969 - 2001.

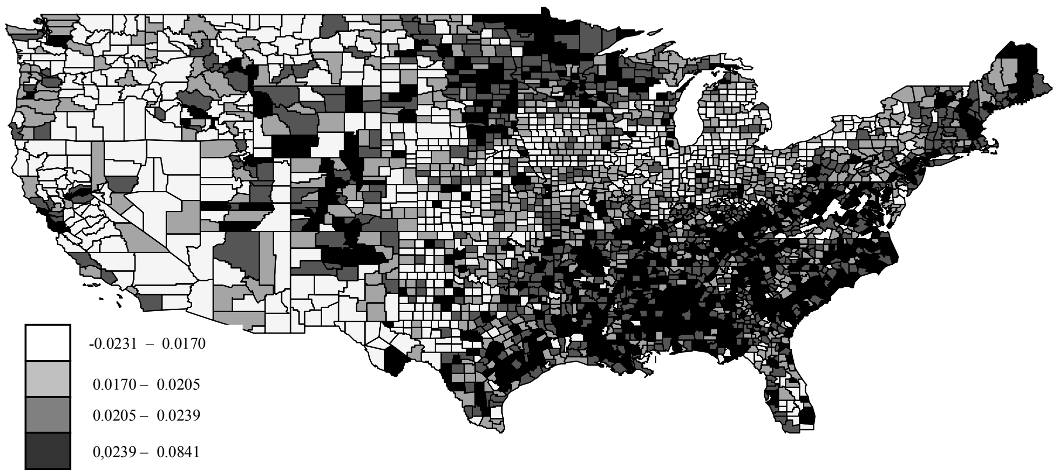


Figure 5. Quantile map of real percapita income growth LISA statistics.

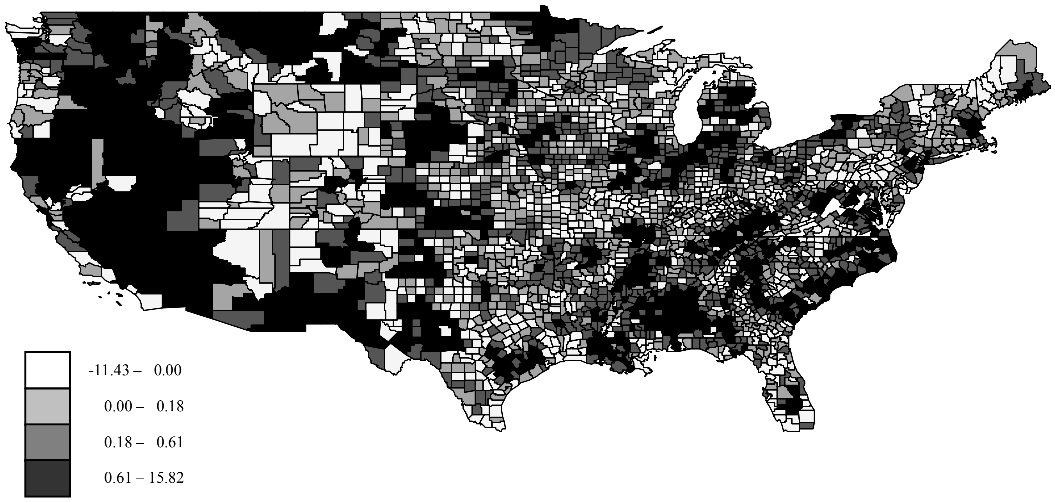
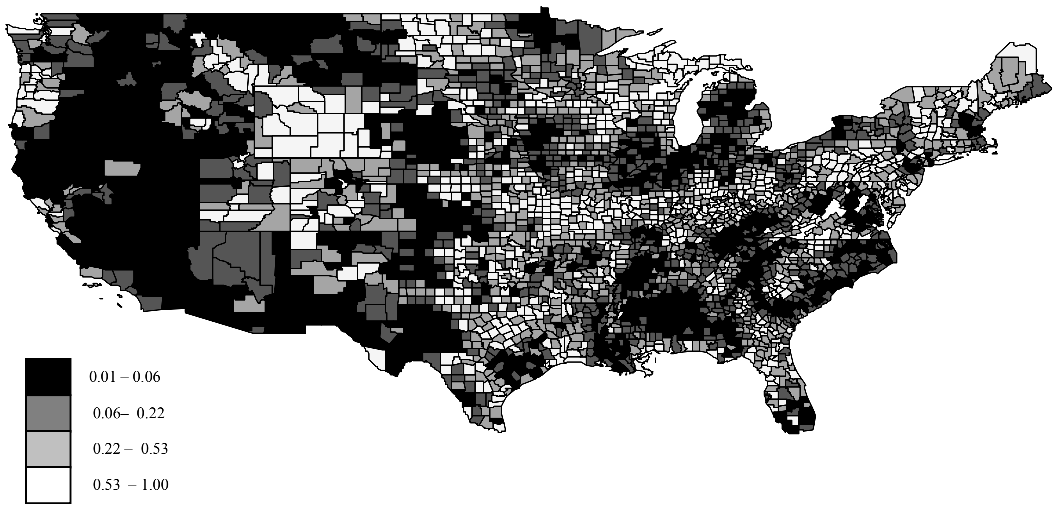


Figure 6. Map of real percapita income growth LISA statistic significance.



[i] For example Krugman (1991) presents some interesting examples of random events leading to GC. Ellison and Glaeser (1997) show that GC of industries due to natural advantages also represents a significant part of the story.

[ii] Their empirical model is as follows:

$$\log \frac{Q_S}{N_S} = \log \Phi + \eta \log h_S + \log D_S(\theta) + u_S$$

where Q represents total product, N total workers, D the density index, θ the product of the two elasticities, η the elasticity of education, and the suffix s denotes the aggregate level (state level). The estimation results suggest that doubling the employment density in a county would lead to an increase in productivity of about six percent. They show that workers in New York, the densest county in the U.S., are 22 percent more productive than the New York state workers. They also found the average output per worker in the ten most productive states to be one-quarter higher than in the ten least productive states.

[iii] Similar results were obtained in previous studies, and Rey and Montouri (1999) concluded that this is enough evidence that the spatial specification is the best model.