Convergence in Mississippi: A Spatial Approach.

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ABSTRACT

Mississippi makes an interesting case study for analyzing the income convergence process because of several characteristics, such as the fairly large number of counties, its relative homogeneous economy and its low percapita income compared with the rest of the U.S. This study analyzes the convergence process at county level, from both a descriptive and general test perspective, applying a spatial statistics framework. It finds evidence of low but significant spatial correlation, suggesting an almost pattern-free spatial distribution of percapita income growth. It also finds significant evidence of β convergence, albeit at a low speed (less than one percent).

R11. Regional convergence Spatial distribution Spatial models

INTRODUCTION

One of the most intriguing research topics, designated by some researchers as the "regional scientist's art" (PLANE 2003, p105), is the permanent growth and change at the regional level. Indeed, the question if inequalities between different regions (countries and their subdivisions) tend to decrease over time, and whether the process is endogenous, always preoccupied economists. Moreover, countries such as Singapore demonstrated that fast growth rates increases are not only possible, but in certain conditions can lead to economic wonders. Understanding these conditions could bring valuable knowledge for policy making.

But, while there are many models describing growth (i.e. RAMSEY 1928, SOLOW 1956, SWAN 1956, KRUGMAN 1991 and 1993, to name only a very few), they are country, region or two-region oriented, and therefore less practical for general analysis. Consequently, although research in the economic growth area is common, the state of theory does not yet provide researchers with a recognized theoretical framework (REY 2001), and the econometric issues underlying the topic are still highly debated. Thus some scholars plead for moving from general tests to "statistical descriptions of what is happening coupled with a forecasting mechanism" (CARVALHO and HARVEY 2002).

This study analyzes β convergence for real percapita income within an U.S. state, namely Mississippi, over the 1969 – 2001 period, combining both a descriptive and a general test perspective. Mississippi has a mix of characteristics that makes such a study interesting. First, the large number of counties (82) provides a fair empirical sample. Second, the absence of trade barriers of any kind (including the less important interstate barriers) as well as the high degree of homogeneity in many other respects, allows for an absolute convergence approach. Furthermore, the problem of different standards and imperfect conversions amongst the data, which may lead to biases (DOWRICK and NGUYEN 1989, DOWRICK and QUIGGIN 1997), is also avoided. Indeed, there should be little reason to distinguish between conditional and absolute convergence in this case (BARRO and SALA-I-MARTIN 1992, CARVALHO and HARVEY 2002). Third, the low percapita income compared with the U.S. also makes Mississippi an interesting case, since extremes are known to behave unpredictably.

The study finds a relatively low level, albeit significant, of spatial correlation within the area. Mississippi seems to be characterized by an almost pattern-free spatial distribution of income growth. It displays a low number of spatial outliers and a relatively low number of spatial clusters, with the largest one being composed out of six low-growth regions situated in the southern part of the state, in the immediate vicinity of the Gulf of Mexico. Tests against the OLS or spatial error model as the best specification for a general convergence test seem inconclusive, although they appear to favor the spatial model. However, relatively strong support for absolute convergence is found, even if at a low speed (less than one percent).

The next section reintroduces the reader to some basic convergence concepts, and the most common model specifications as well as their interpretations. The section also highlights some relatively new spatial analysis concepts that become more and more common in regional science and related fields. The study continues with a short presentation of the data and its sources and with an exploratory data analysis (EDA) and an exploratory spatial data analysis (ESDA) section. After presenting and commenting on the estimation results, the study ends with conclusions and suggestions for further research.

CLASSICAL CONVERGENCE

Theory

The concepts used in classical convergence studies can be illustrated mathematically as follows. The average growth rate of variable *Y,* corresponding to the time interval [*t, T*], may be expressed as (BARRO and SM 1992):

$$\frac{\ln y_{t+T} - \ln y_t}{T} = g + \frac{1 - e^{-\beta T}}{T}\left(\ln(\hat{y}^*) - \ln(\hat{y}(0)\right) \qquad (1)$$

where y represents the percapita (or per effective worker, or per hour worked) level of income (or other analogous indicator) Y, g represents the exogenous rate of growth of the technological progress, $\hat{y}^*$ represents the steady state of the economy, and $\hat{y}(0)$ its initial value, both in intensive form. It is easy to see that in this model y's average rate of growth depends on both β and the distance between the initial and the steady state of the economy. Indeed, the larger β and the distance between the initial level and the steady state level, the higher the average growth rate.

It is said that absolute β convergence exists when poor economies tend to grow faster than the rich ones while all possible factors that govern the phenomenon are endogenous (BARRO and SM 1992, SM 1996). To model such a situation one would assume that $\hat{y}^*$ has a common value for all economies under study and therefore the growth rate depends only on $\hat{y}(0)$, as suggested by BAUMOL (1986). Then, if the coefficient of $\hat{y}(0)$ is statistically significant, one may conclude that the sample exhibits absolute convergence.

On the other hand, conditional convergence exists when there are other variables influencing the speed of convergence, and these variables differ between economies, being therefore area specific. Such variables may lead to different steady states $\hat{y}^*$ and therefore the growth rate for each economy would depend not only on the initial conditions but also on these variables. Finally σ convergence occurs when the dispersion of the real income (or other measure of economic relevance) of a group of economies tends to decrease overtime (SM 1996). It can be demonstrated that β convergence is a necessary but not sufficient condition for σ convergence (SM 1990, BARRO and SM 2004).

While the theory seems straightforward, the empirical results are highly dependent on the methodology and sample, leaving enough room for dispute (see different points of view expressed by ISLAM 1995, QUAH 1996, EVANS and KARRAS 1996, and for a review TEMPLE 1999). Since these alternative methodologies lead sometimes to different values for the speed of convergence, and even to different conclusions regarding the presence or absence of convergence, it seems that the theory is still unable to describe the phenomenon. However, analyzing the convergence process for homogenous groups of economies is more likely to avoid misspecifications due to missing variables, and using common methodologies for different regions allows for easier comparison between studies.

Model specification

One of the simplest empirical specifications for a model allowing testing for convergence was proposed by BAUMOL (1986) and is the starting point for many contemporaneous studies. While the theory behind it might have been less formal (from both an economic and econometric point of view) it is simple and provides a robust study framework. Moreover, it was demonstrated later that the model is in line with economic theory. Ignoring the economy subscript (*i*) the model is:

$$\frac{\ln y_{t+T} - \ln y_t}{T} = \alpha - \beta^* \ln(y_t) + \varepsilon \qquad (2)$$

where:

$$y_t = \frac{Y_t}{L_t} \qquad (3)$$

and where Y represents income, L labor, and T the time interval under analysis. The norm in the literature is to compute the growth rate over the entire time period for which data is available and annualize it, and to standardize income by division to population, number of active workers, hours worked, or other indicators. Then, obtaining a statistical significant β^* is interpreted as evidence that areas with lower income at the beginning of the period (time t) grow faster. Since the average growth rate depends *only* on the initial y, such evidence would indicate *absolute convergence*. The underlying convergence speed is obtained from the following formula:

$$\beta = -\frac{\ln(1-\beta^* T)}{T} \tag{4}$$

The convergence speed was found to be somewhere between 1.5 and 3.0 percent by several previous studies (for various regions and time intervals).

But even if the economy under scrutiny is homogenous enough to be analyzed under an absolute convergence assumption, an important effect may be introduced by the possible spatial dependence in the data. Whilst spatial dependence only relatively recent begun to play an increasingly explicit role in economics and econometrics (ANSELIN 2002a), several scholars 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 1996). Consequently, the classical convergence tests might need to be augmented to take in consideration possible spatial dependencies. Such possible "spatial" models may be (but are not limited to) a spatial Durbin or spatial error model. The decision between the best specifications relies as usual on theory and econometric tests, and several recent papers describe such approaches (ANSELIN 2002b).

Without going into too much detail a model of the form (in matrix specification):

$$y = X\beta + \varepsilon \tag{5}$$

which does not take in consideration the possible influence of the neighboring economies may be amended to reflect such interactions in several ways. The most common specifications are the spatial lag and spatial error models. In the spatial lag model (or spatial autocorrelation model) the spatial dependence is modeled as:

$$\varepsilon = \gamma W y + u \tag{6}$$

where 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 2002b). Accordingly, the error in (4) is considered to be dependent on the values of the dependent variable in the neighboring areas and, estimating such a model without taking in consideration this dependence, would be similar to estimation in the presence of autocorrelation in the case of time series, with the same effects.

A second possible model would be a spatial moving average specification of the form:

$$\varepsilon = \lambda W u + u \tag{7}$$

where λ is the spatial moving average parameter. It should be noted however that both models introduce heteroscedasticity even if it is not present in the initial process (ANSELIN 2002b). The spatial lag model is appropriate when the researcher attempts to quantify the strength of the spatial dependence, while the spatial error model is appropriate only when one aims at correcting the potential bias introduced by the spatial dependence in the original model (ANSELIN 1999).

The framework for assessing the degree of spatial interaction in the data is again somewhat similar to time series data procedures. One of the most common statistics for spatial dependence is Moran's I (MORAN 1950) which aims at identifying departures from random spatial distributions. The formula is:

$$I_t = \left(\frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \right) \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} x_{i,t} x_{j,t}}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{i,t} x_{j,t}} \tag{8}$$

where n is the number of areas and x represents the value of the variable of interest in a certain area. As can be seen from the formula, the statistics is a weighted correlation coefficient where the weights reflect geographic proximity. As in the case of autocorrelations, if the statistics is significant its sign represents the nature of the spatial dependence. Accordingly, a negative significant value indicates negative spatial correlation.

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

$$I = \left(\frac{x_i}{\sum_{i=1}^{n} x_{i,t}^2} \right) \sum_{j=1}^{n} w_{i,j} x_{i,t} \tag{9}$$

and it is a measure of local similarity (dissimilarity). A large positive value of I signals a local set of similar values in the neighborhood (around region i) while a significant 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. Based on the LISA statistics one can classify clusters as high-high (clusters formed by areas with high values of x), high-low (areas with high values surrounded by areas with low values of x), low-high (the inverse of the previous case) and low-low (areas with low values of x). Both statistics are widely used in the literature, and the only possible drawback is the need to decide their statistical significance based on Monte Carlo randomizations. However specialized software is easily available and therefore the analysis does not pose any problem (see for example the commercial packages ClusterSeer and SpaceStat and the free packages GeoDa, and STARS).

DATA AND MODEL ESTIMATION

Data

The data used in this study is compiled from the REIS system of the Bureau of Economic Analysis (BUREAU of ECONOMIC ANALYSIS 2003), and consists of yearly realizations of "Personal income" and "Population" for the 1969 – 2001 interval. The data and methodology is described in the CD-ROM notes and on the web, and therefore need not be discussed here. The "Personal consumer expenditure: Chain-type price index" was used as a deflator for calculating real percapita income. The data is relatively well known, being used in several other studies (BOASSON 2002, HIGGINS et all. 2003). However, the dataset seems underutilized for research, maybe due to the database format, which is less practical for extracting time series data.

Exploratory data analysis (EDA) is usually instrumental for better understanding the underlying structure and relationships in the dataset. Figure 1 reveals the logarithm of real percapita income (LRPI) for the period of study, which, as expected, exhibits an upward trend. The values corresponding to the time interval boundaries are 9.0100 and 9.7272 respectively, which relate to an annual growth of about 2.24 percent. This value is slightly higher then the U.S. aggregate growth of about 2.1 percent. Since the average real percapita personal income in Mississippi is lower than the national one, this by itself is an indication that Mississippi and U.S. real percapita income are converging.

Figure 1 about here. Figure 2 about here.

The corresponding coefficient of variation in Figure 2 exhibits an abrupt drop before 1975, and a slight upward trend after that up until 1995. The last period of the long 1991 – 2000 expansion is marked by a significant upsurge, suggesting an increase in the dispersion of LRPI and therefore a period where convergence is less likely to be present. Although more analysis is needed in order to qualify this behavior, it appears that the coefficient tends to increase during expansions. The observation seems logical if one assumes that the counties with lower economic activity benefit less from an expansion, but are hurt less during a recession. Finally, Figure 3 suggests a negative relationship between the initial LRPI and the real percapita income growth (LRPIGR), and therefore possible convergence. The possible outlier in this case is Madison, but it can be seen that its influence on β^* is negligible.

Figure 3 about here.

In this study the exploratory spatial data analysis is focused on understanding the patterns of spatial correlation in the data and identifying the possible spatial clusters. Figure 4 reveals the map of the LRPIGR values, which helps one visualize the counties with the highest and lowest growth, as well as possible spatial patterns in the data. The county with the largest average annual growth (3.8 %) is Madison, situated in the middle of the state. It is interesting to observe that the counties where gambling became an important part of the economy (gambling was established in late 1990s in Tunica, Coahoma and Bolivar, and the growth of the industry was astonishing) seem to have benefited since they are in the group of counties with relatively high growth. As expected, the counties with the lowest growth are situated mostly in the Mississippi Delta. Interestingly however, the counties neighboring the Gulf of Mexico are in the low growth group, although one would expect their economy to be dynamic due to their location.

<u>Figure 4 about here.</u>

As mentioned above, the degree and significance of the global spatial correlation in the data is assessed with the help of the Moran's *I* statistics. Mississippi's spatial neighborhood structure is characterized by an average of 5.48 neighbors for each county (based on the queen neighborhood definition). The computed Moran's *I* is .1768, with a *p* value of about .002 after 999 Monte-Carlo randomizations. Corresponding to the above Moran statistics, the standard deviation for the LISA statistics is .4551. Table 1 shows the locations that qualify as possible outliers regarding the spatial distribution of the LISA statistics as well as the associated *p* value. The outliers were established with the two times standard deviation rule. There are three such locations, out of which only Scott County has a negative Local Moran value (indicating negative spatial correlation). Naturally, all outliers also appear as possible clusters in the analysis.

<u>Table 1 about here.</u>

Figure 5 shows the map of the clusters (as suggested by the LISA statistics, at a significance level of .05, after 999 randomizations) based on the percapita income growth for Mississippi as well as for the surrounding counties. It appears that, while the overall spatial correlation is significant, there are relatively few clusters. Indeed there are two high-high (Leak and Marshall counties, H-H in the legend), two high-low (Warren and Itawamba counties, H-L in the legend), three low-high (Scott, Lauderdale, and Winston counties, L-H in the legend), and one large low-low (Pearl River, Hancock, Harrison, Jackson, George and Stone counties, L-L in the legend) clusters. The later is the clearest spatial cluster, situated in the southern region of the state and composed by six low growth regions (out of which three are adjacent to the Gulf of Mexico). As it can be observed from the maps the counties surrounding the state border are maintained in the sample throughout the analysis. This approach assures correct statistics for all calculations where a first-degree neighborhood matrix is involved.

Figure 5 about here.

Estimation

There are several examples of studies that looked at different regions and time periods to assess the degree to which the classical convergence framework holds. They employed different methodologies and, as mentioned above, their findings are many times contradictory, but in the case of the U.S. many studies reported convergence at a speed of around two percent (for a review of such studies see BARRO and SM 2004). However, researchers analyzing less homogeneous samples of economies found that divergence may not be ruled out in certain cases, and suggested that the possibility of formation of "clubs" should also be considered (the term "clubs" was coined by QUAH 1996 who suggested that the distribution of growth patterns may be bimodal, or even multimodal). Moreover, they also found that, for certain time periods at least, divergence may appear even within countries, suggesting that relatively similar economies do not necessarily converge (EVANS and KARRAS 1996). Examples of regions exhibiting very weak or no support at all for convergence are Austria (HOFER and WORGOTTER 1997), and Greece (SIRIOPOULOS and ASTERIOU 1988).

Several convergence studies that tested the assumption of spatial autocorrelation in their data, found a spatial econometrics approach to be appropriate. For example REY and MONTOURI (1999) analyzed U.S. state level percapita income data for the 1929 – 1994 period and found significant spatial autocorrelation, suggesting that any estimation overlooking it may be misspecified. They estimated a cross regressive model similar with the one in this study and found a convergence speed of about 1.9 percent, a value very close to the well known two percent. Moreover, they suggest that taking the spatial correlation in consideration improves the specification. The path for deciding if a model should be augmented to take in consideration the possible spatial dependence is again similar to time series methodologies. In the first step a classical OLS regression is performed and the residuals are analyzed with the help of tests such as Moran's *I*, Lagrange multiplier (LM), and Robust LM against alternate specification. Based on the results a spatial model is then considered.

<u>Table 2 about here.</u>

Table 2 reveals the estimation for the "classical" OLS regression as well as for the spatial model believed to fit the data best. The OLS results suggest an acceptable fit for this type of model and data, while the maximum likelihood model brings no significant changes. Moreover, although the diagnostic statistics for the OLS estimation suggest weak heteroscedasticity (White test marginally significant with a *p* value of .0422) and the spatial diagnostic tests suggest a spatial error model (the Moran's *I* *p* value is .0171 and the LM test for the error model has a *p* value of .0330), the Akaike and Schwartz criterion are both slightly larger for the ML model, and the LR test for spatial dependence is only marginally significant (*p* value .0478). However, for the spatial model, the Breusch-Pagan test does not indicate significant heteroscedasticity (*p* value .0563) suggesting a better specification.

Based on the tests presented above it seems difficult to decide which approach fits the data best. However in both cases β^* is highly significant and has a fairly close value, which is taken as a proof that the real percapita income in Mississippi converges. In both cases the speed of convergence is about .8 percent, much less than the two percent which part of the literature suggest as a universal constant. It is also unlikely that employing other methodologies would lead to a different conclusion, but a time-series approach could be instrumental, due to the sample's properties. Indeed, the 80 homogenous economies and the relatively long period of 32 years could provide for a good opportunity to compare the results obtained with different methodologies.

CONCLUSION

This study investigates the convergence process at the county level for Mississippi, for the 1969 – 2001 interval, from both a descriptive and a general test approach. It finds indications of low but significant global spatial correlation, but a relatively low number of spatial clusters, suggesting a spatially unorganized economy. Applying both a classical and a spatial approach, the study finds significant evidence of real percapita income convergence amongst the counties in Mississippi. The convergence speed of about .8 percent however is lower than the two percent speed suggested by other authors as “standard”.

The main limitation of the study may be its methodology. As mentioned above, the debate regarding the appropriate methodology for the so-called general convergence tests is still one of the main issues in this research area, and several serious alternatives are mentioned in the literature (for a review of alternate specifications see TEMPLE 1999 and BARRO and SM 2004). Due to the characteristics of this sample of counties, a panel approach would probably reveal more insight in the dynamics of the process. Also, inclusion of a larger sample of counties (for example counties in Alabama and Louisiana) could allow for a better understanding of the convergence process in this part of the nation and possibly reveal spatial patterns.

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Table 1. LRPI spatial distribution outliers.

FIPS	County	State	LISA	*z*-score	*p*-value
28045	Hancock	MS	1.1983	2.4803	0.0131
28047	Harrison	MS	1.1050	2.2885	0.0221
28123	Scott	MS	-0.7975	-2.1733	0.0298

Table 2. Estimation results.

Variable	OLS		ML	
	Coefficient	***t*-stat.**	**Coefficient**	***t*-stat.**
Constant	0.1132	7.1436	0.1109	6.7094
LRPI 1969	-0.0098	-5.5894	-0.0095	-5.2165
Lambda	-	-	0.2654	2.0782
R^2		0.2066		0.2434
F statistics		31.2414		-
AIC		-1010.49		-1014.54
SIC		-1004.88		-1008.93

Note: As in (7), lambda stands for the coefficient of the lagged error.

Figure 1. Log of real percapita income, 1969 - 2001.

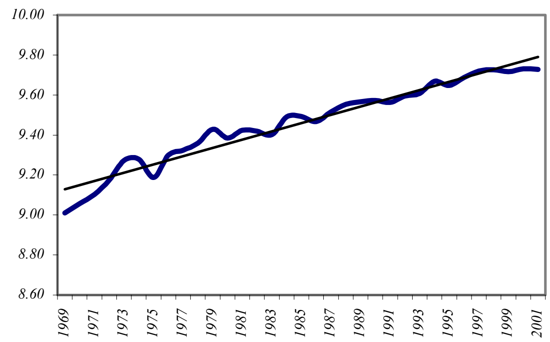

Figure 2. Coefficient of variation LRPI, 1969-2001.

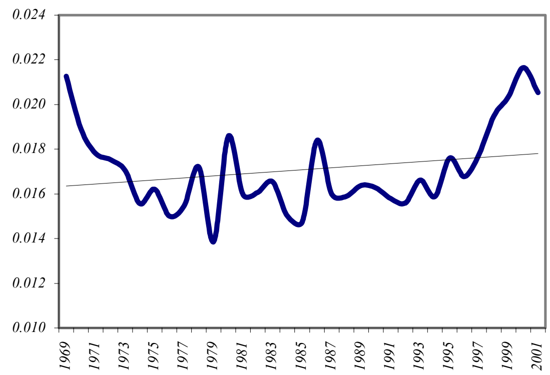

Figure 3. Growth scatter plot, 1969-2001.

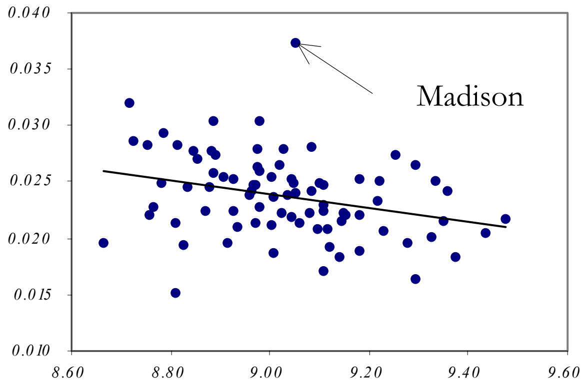

Figure 4. Spatial distribution of real percapita income growth.

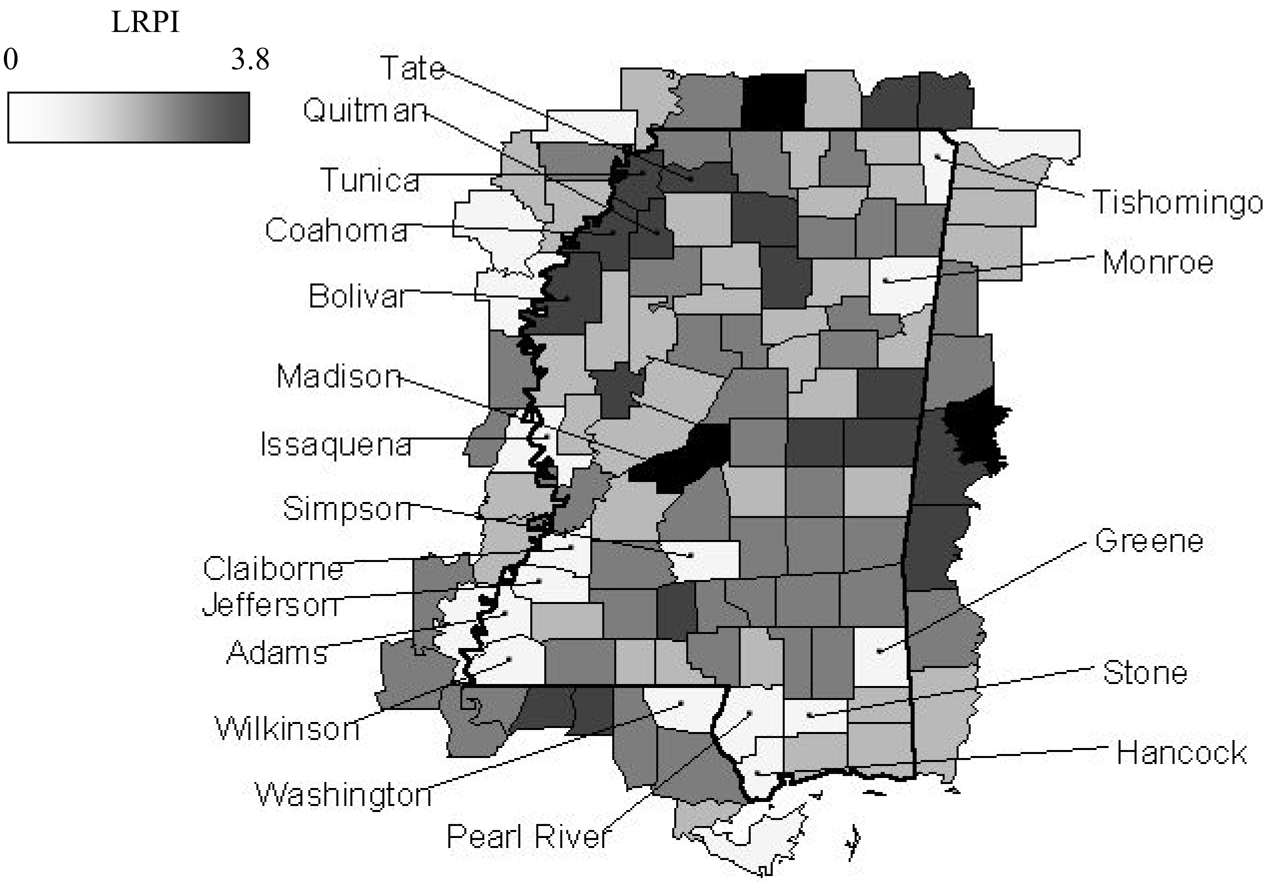

Figure 5. Cluster Map, real percapita income growth.