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Regional Disparities in the Spatial Correlation of State Income Growth, 1977-2002

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Abstract

This paper presents new evidence of spatial correlation in U.S. state income growth. We extend the basic spatial econometric model used in the growth literature by allowing spatial correlation in state income growth to vary across geographic regions. We find positive spatial correlation in income growth rates across neighboring states, but that the strength of this spatial correlation varies considerably by region. Spatial correlation in income growth is highest for states located in the Northeast and the South. Our findings have policy implications both at the state and national level, and also suggest that growth models may benefit from incorporating more complex forms of spatial correlation.

Keywords: economic growth, per capita income, spatial econometrics

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Regional Disparities in the Spatial Correlation of State Income Growth

1. Introduction

In recent years, it has become common to use spatial econometric techniques to investigate the role of location as a determinant of economic growth (see Abreu *et al*. (2004) for a survey). From the estimation of a variety of cross-country and sub-national models, the literature has generally concluded that a country or region's growth can be substantially dependent on the growth (or lack thereof) of other countries or regions.

Although the models of spatial correlation appearing in the literature do vary, they all share a common characteristic in that they restrict potential spatial correlations between countries or regions to be the same across all geographic divisions in the sample. Evidence of regional differences in economic performance during national business cycles and in response to economic integration both in the European Union and United States suggests, however, that the influence of spatial correlations among neighbors could vary across regions.[1] In this paper we extend the typical spatial econometric model of growth to allow for regional variation in spatial correlations. We estimate the model using data on U.S. states, for which control variables have been extensively researched (see Crain and Lee, 1999) and where measurement problems are less thorny than with a cross-country study.

Consistent with the broader literature, we find evidence of positive spatial correlation in state-level income growth across the United States as a whole. That is, when spatial correlation is assumed to affect all states equally, we find that a given state's income growth is directly related to the income growth of its neighbors. However, when we allow for regional differences in the impact of spatial correlation in state income growth, we find large and statistically

[1] See DeJuan and Tomljanovich (2005), Barrios and de Lucio (2003), and Carlino and Sill (2001) for a review of recent work in this area.

significant differences across regions in the effects of spatial correlation. Since the regional-specific spatial models also "fit-the-data" better than the standard models with common spatial effects, our results suggest that more complex forms of spatial correlation may be at work in growth dynamics.

2. Literature Review

Although the connection between location and growth is deep-rooted, DeLong and Summers (1991) were the first to discuss the possibility that spatial patterns may exist in standard cross-country growth regressions. They observed that since omitted variables in neighboring countries are likely to take on similar values, citing the similarities between Belgium and the Netherlands as an illustration, the residuals from a 'standard' growth regression could be correlated across countries. Although DeLong and Summers (1991) found no evidence of spatially correlated residuals in their data, their recognition of the potential for spatial correlation prompted further examination. Over the past several years, the notion that location can affect growth has evolved to reflect the broader view that direct and indirect linkages between regions or countries are important in understanding growth dynamics.

For instance, economic growth in a region or country can be influenced by regional business cycles, flows of trade, capital, and migration, as well as political instability and armed conflicts, technology diffusion, access to product and input markets, and common economic, political, and social arrangements (Moreno and Trehan 1997; Ades and Chua 1997; Ramirez and Loboguerrero 2002; Ying 2005). From a more practical perspective, Rey and Montouri (1999) also discuss the possibility that boundary mismatch problems can produce spatial correlation. Such a problem arises when the economic notion of a market does not correspond well with the geographical boundaries used for data collection. For instance, the "true" labor market of a metropolitan area that is located in one state, but borders one or more other states, could easily encompass a multi-state area.

While spatial correlation in cross-sectional regression models might be mitigated by including additional control variables, the problem is often more difficult to address in practice because of measurement issues and complex spatial correlations (Anselin 1988). In addition, failing to correct for spatial correlation can result in either biased and inconsistent, or inefficient parameter estimates, depending on the nature of the correlation (Anselin 1988).

Spatial correlation is usually addressed using explicit spatial econometric techniques. In the growth literature, the use of spatial techniques has focused almost exclusively on the estimation of either a spatial lag or a spatial error model (Abreu *et al*. 2004). Spatial lag models allow for spillovers in the dependent variable and spatial error models permit correlation in model errors across geographic units.

As Abreu *et al*. (2004) note, a large majority of the studies that use spatial econometric models to examine growth have employed a convergence framework to explore reductions in the dispersion of cross-sectional growth (σ-convergence), and whether poor countries growth faster than rich countries and share a common steady-state growth path (β-convergence). The literature has found evidence in favor of convergence *and* positive spatial correlation (see Abreu *et al*. (2004) for an excellent survey). As an illustration, Rey and Montouri (1999) investigated the spatial aspects of both σ- and β-convergence for U.S. states over the period from 1929 to 1994. They find that personal income growth rates became less disperse over the sample period, which is consistent with σ-convergence. In addition, Rey and Montouri (1999) find evidence of positive spatial autocorrelation in the dispersion of state-level personal income, with "two strong regional clusters" of income growth in the New England and Southeast regions of the United States.

To explore the presence of spatial patterns in β-convergence, Rey and Montouri (1999) modified the basic unconditional convergence framework, which involved regressing the ratio of current-to-initial income on a constant term and initial income, as well as estimating one specification with a spatial lag term and one specification with a spatial error term. The spatial lag specification permits growth in a state's income to depend on the state's initial income and the initial income of neighboring states (those sharing a common border in the framework of Rey and Montouri (1999)), while the spatial error model allows correlation in model errors across states. In both spatial econometric specifications, as well as a baseline model that excludes spatial effects, Rey and Montouri (1999) find evidence to support unconditional β-convergence. The spatial lag and spatial error coefficients are found to be significant at the 1 percent level, with the results of specification tests indicating the spatial error model may be more appropriate. A number of subsequent studies, with a largely European focus, have applied the basic spatial growth framework of Rey and Montouri (1999) and found similar results using a variety of different time periods and geographic focus.[2]

The focus of our paper differs from previous work in two important ways. First, we estimate a short-run model of growth for U.S. states, as opposed to a long-run (i.e. convergence) model. This allows us to not only avoid the potential for structural differences that may arise in a cross-country framework, but also avoid the criticisms of convergence models in general (Quah 1993, 1996). In addition, since convergence models are tested by regressing income growth on initial income, and possibly other control variables, it would seem to be the case that any spatial

[2] See for instance Moreno and Trehan (1997), Ramirez and Loboguerrero (2002), Conley and Ligon (2002), Fingleton (2001), Ying (2003), and Le Gallo (2004).

growth effects uncovered in these models are a result of long-run dynamics. However, with regard to U.S. states, there is considerable evidence to suggest that short-run growth dynamics may also be spatially related. For example, Carlino and Sill (2001) find evidence of regional linkages in the trend and cyclical components of real per capita personal income for Bureau of Economic Analysis (BEA) regions within the United States. Applying a vector error correction model to quarterly data from 1956-1995, Carlino and Sill (2001) find that regional income growth is cointegrated across BEA regions, which indicates that the regions share a common long-run growth path. The linkages are not as strong with regard to the cyclical component, however. The cyclical component of the Far West region is "out-of-synch" with the cyclical components of the nation and other regions (the Far West has a simple correlation of 0.36 with the nation, compared to an average of 0.97 for the other regions). From the perspective of growth regressions, these findings suggest that while sub-regions of the U.S. appear to converge, there is reason to suspect the presence of spatial correlation in transitory deviations from trend. Thus, a transitory shock that affects growth in a given state may affect growth in other states, and the strength of the spillovers may differ across sub-regions of the United States.

A second difference between our study and prior work is that we allow spatial correlation in state income growth to vary across regions of the United States. Carlino and Sill's (2001) finding of regional cyclical components in state income growth suggests regional heterogeneity in the influence of spatial effects. An apparent difference in the influence of changes in monetary policy across regions (Carlino and DeFina, 1999) is one possible reason for this heterogeneity. Prior research has found evidence of regional heterogeneity in agriculture and state bank regulatory policies (e.g., Garrett, et al., 2003) but regional differences in the spatial correlation of state economic growth has not been explored. The advantage of allowing any spatial correlation in state income growth to vary across regions is that we are able to formally test for regional disparities in state income growth. The possibility of regional differences in spillovers in state income growth has implications for both state and national policies that effect economic growth.

3. Data and Empirical Specification

We use the basic model of spatial correlation developed by Cliff and Ord (1981) and Anselin (1988) to investigate the determinants of state-level annual income growth in the 48 contiguous states over the period 1977 - 2002.[3] The general spatial model allows for potential spatial correlation in both the dependent variable and error term. It does not induce cross-sectional correlation if none is present; it simply provides an established and flexible framework for relaxing the assumption of cross-sectional correlation with regard to a model's dependent variable and/or error term. As Anselin (1988) notes, unlike time-series correlation that is one dimensional, spatial correlation in cross-sectional models is multi-dimensional in that it depends upon all contiguous or influential units of observations (in this case states). Formally, the general first-order spatial model may be expressed as:

$$y = \rho \boldsymbol{W} y + \boldsymbol{X}\beta + \varepsilon \tag{1a}$$

$$\varepsilon = \lambda \boldsymbol{W}\varepsilon + \nu = (I - \lambda \boldsymbol{W})^{-1}\nu \tag{1b}$$

[3] Because we use Crain and Lee's (1999) measure of industry diversity in our regressions, which is constructed using Gross State Product (GSP) data, the starting date of our sample is limited to 1977 because this is the first year that GSP data are available.

where y is the (TN×1) vector of growth rates in real per capita state personal income and $\boldsymbol{X}$ is a (TN×K) matrix of regressors. The spatial lag component is given by $\rho \boldsymbol{W} y$, where $\boldsymbol{W}$ denotes the exogenous (TN×TN) block diagonal matrix composed of the (N×N) spatial weights matrices $\boldsymbol{w}$ along T block diagonal elements. The scalar ρ is the spatial lag coefficient that must be estimated. Positive spatial correlation exists if $\rho > 0$, negative spatial correlation if $\rho < 0$, and no spatial correlation if $\rho = 0$.[4] The spatial error component of the model is given by $\varepsilon = \lambda \boldsymbol{W} \varepsilon + \nu$, where ε is a (TN×1) vector of error terms, $\boldsymbol{W}$ is the (TN×TN) matrix previously described, ν is a (TN×1) white noise error component, and λ is the spatial error coefficient that must be estimated. The errors are positively correlated if $\lambda > 0$, negatively correlated if $\lambda < 0$, and spatially uncorrelated correlated if $\lambda = 0$. Note that if no spatial correlation of any form exists, then $\rho = \lambda = 0$ and the general spatial model reduces to the standard regression model.

Since the spatial lag term in Equation (1a) is correlated with the error term and the spatial error component is also non-spherical, ordinary least squares (OLS) estimation of Equations (1a) and (1b) will result in biased, inconsistent, and inefficient parameter estimates (Anselin 1988). Assuming the random component of the spatial error (ν) is homoskedastic and jointly normally distributed, Equations (1a) and (1b) can be estimated by maximum likelihood. Anselin (1988) derives the log-likelihood function for the general spatial model, which can be expressed as:

[4] Unlike the standard first-order autoregressive model in time series, the spatial correlation coefficients do not necessarily have to lie between –1 and 1 in the first-order spatial autoregressive model. Generally, when a binary weights matrix is used the values for the spatial correlation coefficients are between the inverse of the largest and smallest eigenvalues of the weights matrix. See Anselin (1995).

$$\ell = -\left(\frac{NT}{2}\right)\ln(\pi) - \left(\frac{1}{2}\right)\ln\left(\sigma_\nu^2\right) + \ln\left|\boldsymbol{I} - \rho\boldsymbol{W}\right| + \ln\left|\boldsymbol{I} - \lambda\boldsymbol{W}\right| - \left(\frac{\psi'\varphi'\varphi\,\psi}{2\sigma_\nu^2}\right), \tag{2}$$

where $\psi = y - \rho\boldsymbol{W}y - \boldsymbol{X}\beta$, $\varphi = \boldsymbol{I} - \lambda\boldsymbol{W}$, and $\boldsymbol{I}$ is a TN×TN identity matrix.

The cross-sectional spatial weights matrix (***w***) formalizes the potential correlation among states for which many alternative representations have been used in the literature. We consider two specifications of ***w*** in our empirical analyses. First, a common weights matrix in the growth literature (and spatial econometrics literature in general) is the binary contiguity matrix (Cliff and Ord, 1981; Anselin, 1988; Case, 1992). In this representation, the individual elements of ***w***, denoted ω_{ij}, are set equal to unity if states *i* and *j* ($i \neq j$) share a common border, and to zero otherwise. The limitations of this specification are that all neighboring states are assumed to have equal influence and any spatial correlations beyond common-border neighbors are ignored.[5]

In addition to a common-border weights matrix, we also consider distance as an alternative spatial weighting scheme. Distance-based weighting has been used in several studies, such as Dubin (1988), Garrett and Marsh (2002), Hernandez (2003), and Garrett *et al*. (2003), but has not been widely exploited in the growth literature. The most established distance-based weighting scheme, and the one we implement in this paper, is an inverse distance format where $\omega_{ij} = 1/d_{ij}$, and d_{ij} is the distance between states *i* and *j*. In addition, $\omega_{ij} = 0$ for $i = j$. Thus, as the distance between states *i* and *j* increases (decreases), ω_{ij} decreases (increases), which gives less (more) spatial weight to the state pair when $i \neq j$. Since there is no consensus in the literature on how distance should be measured, we follow Hernandez (2003) and measure distance as the

[5] We follow the established practice of row-standardizing the contiguity weight matrix by dividing each ω_{ij} by the sum of each row *i*.

difference between state population centers.[6] This weighting scheme is very intuitive and extends any potential spatial correlation beyond common-border neighbors since all states are spatially related, but nearer states (measured by the proximity of their population centers) have a greater potential influence.

The basic spatial model detailed above assumes that the influence of spatial correlation is the same for all states. That is, the functional form given by Equations (1a) and (1b) does not permit regional differences in either the spatial lag or spatial error. We modify Equations (1a) and (1b) to allow for different spatial correlation coefficients in different regions of the United States. We use both region and division classifications by the U.S. Bureau of the Census. There are nine Census Bureau divisions in the contiguous 48 states and four regions. The spatial model with regional spatial correlation coefficients may be written as:

$$y = \sum_{k=1}^{R} \rho_k \boldsymbol{W}_k y + \boldsymbol{X}\beta + \varepsilon \tag{3a}$$

$$\varepsilon = \sum_{k=1}^{R} \lambda_k \boldsymbol{W}_k \varepsilon + \nu = (I - \sum_{k=1}^{R} \lambda_k \boldsymbol{W}_k)^{-1} \nu\,, \tag{3b}$$

where R denotes the total number of regions, and ρ_k and λ_k denote the spatial lag and spatial error lag coefficients, respectively, for region k. $\boldsymbol{W}_k$ remains the (TN×TN) block diagonal matrix having (N×N) spatial weights matrices $\boldsymbol{w}_k$ along T block diagonal elements. Each matrix $\boldsymbol{w}_k$ is constructed by pre-multiplying by a dummy variable that equals unity if state i is located in region k, and zero otherwise.[7] This provides a different interpretation of $\boldsymbol{w}_k$ depending upon whether $\boldsymbol{w}_k$ is a contiguity weight matrix or a distance weight matrix. In the case of a contiguity matrix, we allow growth in state i located in region k to be affected by the income growth of all

[6] The distance was computed using the geographic coordinates for the population centroids computed by the Bureau of the Census for the year 2000. Population centroids did not differ significantly in early decades.

[7] Note that this specification allows for asymmetry in spatial correlation between two states each located in a different region. That is, if states i and j are in different regions, then the spatial effect of i on j could be different than the spatial effect of j on i.

states *j* that border state *i*, regardless of whether state *j* is in the same region as state *i*. With the distance weights matrix, the elements of each matrix $\boldsymbol{w}_k$ capture spatial correlation between each state in region *k* and the remaining 47 states. Thus, for each state *i* in region *k*, row *i* of distance matrix $\boldsymbol{w}_k$ contains some measure of distance between state *i* and all remaining 47 states. If state *i* is not in region *k*, then row *i* of distance matrix $\boldsymbol{w}_k$ contains all zeros.

The matrix (***X***) includes variables that Crain and Lee (1999) have shown to significantly affect state income growth. They use an Extreme-Bounds Analysis (EBA) to test the robustness of 29 different control variables in growth regressions for the 48 contiguous U.S. states over the period 1977-92. We use the independent variables that Crain and Lee (1999) identify as robust determinants of state income growth. These are the share of a state's population between the ages of 18 and 64, the share of a state's population with at least a bachelor's degree, a measure of a state's industrial diversity, government expenditures as a proportion of state gross product, and local government revenue as a share of state and local revenue. Crain and Lee (1999) find that the population and educational attainment variables, which they argue control for the size and skill of the labor force, have a positive effect on growth. On the other hand, states with broader industrial bases, larger governments, and those that collect more revenue at the local level are found to experience significantly slower growth. Crain and Lee (1999) contend that the local governments' revenue share may proxy for the degree of fiscal centralization or intergovernmental competition within a state.

We include one additional control variable in our model that was not a product of Crain and Lee's (1999) Extreme Bounds Analysis. Recent evidence suggests that the relaxation of state laws restricting interstate banking and intrastate bank branching during the 1970s and 1980s may have had a large impact on the growth rate of state income (Krol and Svorny 1996; Jayaratne and

Strahan, 1996; Strahan, 2003). Jayaratne and Strahan (1996) argue that deregulation substantially improved bank performance by reducing operating costs and loan losses, and estimate that deregulation permanently increased a state's real income growth rate by some 0.50 – 1.00 percentage points. Such large, permanent growth effects have not gone unchallenged, however. Further, Wheelock (2003) notes the presence of spatial patterns in state banking regulatory decisions, while Freeman (2002) finds that states were more likely to deregulate banking when income growth was below trend. Given this unresolved, yet potentially large, linkage between bank deregulation and growth, we include an indicator variable in our model that equals unity beginning in the year a state first permitted state-wide branch banking, and zero otherwise.[8]

We follow Crain and Lee (1999) by estimating our models with all variables specified as first difference of logs, except for the bank deregulation dummy variable. This eliminates the potential problems of non-stationary variables and state-specific serial correlation. Complete variable descriptions, data sources, and descriptive statistics for our variables in levels and first difference of logs are provided in Table 1.

[Table 1 about here]

4. Empirical Results

We estimate various specifications of the spatial models described above using both a contiguity spatial weights matrix and an inverse distance spatial weights matrix. Table 2 presents the results from the specifications that assume no regional differences in spatial effects. Column 1 shows the results from the basic Crain and Lee (1999) growth regression with no

[8] We explored the possibility that a state's banking deregulation decision may be endogenously determined with income growth, but did not find evidence to support this view.

spatial effects (i.e. $\rho = \lambda = 0$). We also estimate a spatial lag model, spatial error model, and spatial lag and error model using both weights matrices for a total of six spatial models. The estimates from the spatial lag models are presented in Columns 2 and 3. Columns 4 and 5 present the spatial error results, and Columns 6 and 7 report the specifications containing both a spatial lag and spatial error.

[Table 2 about here]

The basic OLS specification in Column 1 is largely consistent with the findings of Crain and Lee (1999), and the independent variables explain 54 percent of the variation in state income growth. We find, for example, that state income growth is positively correlated with the size of a state's labor force, and that states with larger government sectors, more industrial diversity, and those that collect more revenue at the local rather than state level experience significantly slower income growth. We also find that growth is uncorrelated with educational attainment.[9] In addition, we find little evidence that bank deregulation results in significantly higher growth, which is consistent with Freeman (2002; 2005).

Consistent with the growth and convergence literature, the results reported in Columns 2 – 5 of Table 2 reveal strong evidence of spatial correlation. Furthermore, regardless which weights matrix we use, the coefficients on ρ and λ are quite similar in magnitude and statistically significant at the 1 percent level. The estimated spatial lag coefficients are all positive, indicating that a state's income growth is directly affected by the income growth of neighboring states. The estimates of ρ from columns 2 and 3 indicate that a one percentage point increase in the average income growth of 'neighboring' states generates a 0.23 percentage increase in state *i*'s

[9] Although Crain and Lee (1999) classify educational attainment as a "core variable," they find it to be a significant determinant of growth only in their baseline regression, which includes just one other variable – labor force size.

income growth rate, regardless whether 'neighboring' states include only the states that share a border with state *i* or all states, with nearer states having more influence.

In contrast to ρ, the interpretation of λ is analogous to an estimate of first-order serial correlation in a time-series regression. The positive and significant estimates for λ that appear in Columns 4 and 5 indicate that there is evidence of significant positive residual correlation across space, which could be due to spatial heterogeneity or omitted variables. However, the Akaike Information Criterion (AIC), Schwarz Criterion (SC) and the log-likelihood statistics all reveal that the spatial lag models presented in Columns 2 and 3 provide a better fit than the spatial error models.

The results from the models that include both the spatial lag and error term (Columns 6 and 7) reveal that only the spatial lag coefficients are significantly different from zero and have magnitudes very similar to those presented in Columns 2 and 3. This suggests that the significant spatial error coefficients in Columns 4 and 5 were likely capturing omitted spatial correlation in state income growth. The findings presented in Table 2 suggest that spatial correlation in state-level income growth may be best modeled using a spatial lag. This is supported by the AIC and SC, which are directly comparable across models and weigh the explanatory power of a model (based on the maximized value of the log-likelihood function) against parsimony. Based on the AIC and SC, all of the spatial models are preferred to the OLS specification, but the spatial lag model that utilizes the contiguity weights matrix provides the best fit of the data.

Finally, it is also interesting to note that the inclusion of the spatial effects has little impact on the estimated parameters for the control variables. We find the banking deregulation indicator to be significant at the 10 percent level in Columns 2 and 4 in Table 2, but the magnitude and significance of the remaining independent variables are largely unchanged.

Table 3 presents the results from four specifications that allow for regional differences in the spatial correlation coefficient. Because our results in Table 2 indicate that a spatial lag correction is the appropriate specification, we only consider regional differences in spatial lag coefficients for all regressions shown in Table 3. Appendix Table 1 lists the states that are included in each division and region.

[Table 3 about here]

We report two basic specifications in Table 3; each estimated using both a regional contiguity weights matrix and a regional inverse distance weights matrix, resulting in a total of four models. Columns 1 and 2 report the estimates from the spatial lag model that allows for regional-specific spatial lag coefficients at the Census region level, while Columns 3 and 4 allow for both regional-specific spatial lag coefficients at the Census division level. Both the region and division classifications of U.S. states will be considerably less diverse from an economic perspective, which may add to our insights of spatial patterns in income determination.

The results reported in Table 3 provide strong evidence that spatial correlation in state-level income growth varies substantially by region. The spatial lag coefficients for the four regions are all significant at the 5 percent level or higher. The regional spatial lag coefficients in Columns 1 and 2 indicate that the growth spillovers effects range from a low of about 0.10 in the South to a high of 0.28 in the Northeast. The spatial lag coefficients for the Midwest, West, and South are similar in size (0.10 to 0.14), but the Northeast coefficient is nearly twice as large. This finding may reflect the relatively small size of states in the Northeast and their significantly larger populations, both of which make it likely that that their economies are linked to a greater degree than those of other states. It is also worth noting that the regional-specific models are preferred to the aggregate spatial lag models in Table 2 based on the various measures-of-fit.

The regressions that allow for division level regional spatial coefficients (Columns 3 and 4 of Table 3) provide a slightly different picture than the region level models. The estimated spillover effects are for the most part positive (except for West South Central division), but significant spatial correlation is not present in each division. Estimates of positive and significant spatial correlation in census divisions range from 0.10 to 0.43. We find no evidence of spatial correlation in either the Mountain or Pacific divisions, however, which is interesting given that the spatial correlation for the West region (Columns 1 and 2 in Table 3) is positive and significant and the West region is made up entirely of the Mountain and Pacific divisions. This difference might be associated with sample size, namely that there are relatively fewer states in Census divisions than in Census regions.

States in several divisions appear to be affected more strongly by their common-border neighbors than by all states as a whole. The spatial coefficients in the Middle Atlantic, East North Central, and East South Central are all substantially larger when neighbors are defined by common-border as opposed to inverse distance. On the other hand, the opposite form of correlation may be at work in the West South Central division. There is no evidence of spatial correlation for states in this division when neighbors are defined by common-border, yet we find evidence of negative correlation using the inverse distance weights matrix.

The results from the regional-specific models in Table 3 suggest considerable heterogeneity across regions in the effects of spatial correlations on state income growth. Further evidence is reported in Tables 4 and 5, where we present p-values from pairwise hypothesis tests of the equality of the spatial correlation coefficients from the models in Table 3.

At the region level (Table 4) there are six pairwise equality tests for each regression. Using the common-border neighbor definition, the test results show that the spatial correlation for states in each region is significantly different from the correlation in other regions, with the exception of the South and West regions. With the inverse distance weights matrix, the *p*-values indicate that spatial correlation is not significantly different between states in the South and West, and South and Midwest, but that spatial correlation differs significantly across all other regions.

Heterogeneity in spatial correlation is further evidenced by the equality tests from the division level regressions (Table 5). Of the 36 possible pairwise equality tests at the division level, we find that the spatial correlation is significantly different in 31 tests when neighbors are defined as common-border and in 29 tests when using an inverse distance weighting. The results from the regression results in Table 3 and the pairwise hypothesis tests shown in Table 4 and Table 5 provide strong evidence of spatial correlation in state income growth in most, but not all regions, and that the impact of spatial correlation on state income growth varies statistically significantly across regions of the United States.

[Tables 4 and 5 about here]

5. Conclusion

Although the role of space as a determinant of growth has received considerable attention in recent empirical studies, work in this area has focused almost exclusively on testing convergence hypotheses using international data. In this paper we estimate several spatial econometric models to explore the extent of spatial correlation in the short-run growth dynamics of state personal income in the United States. We use an established set of control variables that are robust determinants of state-level growth to reduce the possibility that any uncovered spatial patterns are the result of omitted variable bias or measurement issues.

Our results provide strong evidence that spatial correlation exists in state-level income growth. The models in which we assume a common spatial lag coefficient for all states, we find that a one percentage point increase in the average income growth of 'neighboring' states generates between a 0.22 and 0.29 increase in a given state's income growth rate, depending on the specification. In addition, this paper is the first to explore whether spatial correlation in state income growth varies for states in different regions of the United States. We find that spatial correlation in state income growth does differ significantly by region, and our model of regional-specific spatial correlations fits the data better than the typical spatial econometric model that assumes a common spatial lag coefficient for all regions. Generally, we find that states in the Northeast and South experience the strongest cross-state income linkages – roughly a 0.20 to 0.40 percent increase in state income growth for every percentage point increase in ‘neighboring’ state income growth. States in these regions are generally smaller and more populous, and thus are more likely to have linked economies, than states in the Midwest and western regions of the country.

The broader implication of our findings is that the spatial correlations at work in income growth dynamics appear to be complex. Further research is warranted to improve our understanding of how various regional forces affect growth dynamics and to uncover the underlying source(s) of such regional forces. Our results suggest that states should pay particular attention to fiscal policies in neighboring states, as state-level fiscal policies can significantly influence income growth in neighboring states. Also, policy makers should realize that improving or deteriorating economic conditions in neighboring states are likely to affect economic growth in their own states.

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Table 1 – Descriptive Statistics

	Levels	First difference of logs	Description	Source
	Mean (Std. Dev.)	Mean (Std. Dev.)		
Personal income	13780.815 (2527.832)	1.392 (2.521)	Real per capita personal income (1982-1984=100)	Bureau of Economic Analysis (BEA)
Labor	60.604 (2.019)	0.234 (0.876)	Share of the state's population between the ages of 18 and 64 (share * 100)	Bureau of the Census
Education	20.251 (5.293)	2.370 (5.063)	Share of the state's population age 25 and older with at least a bachelor's degree (share * 100)	Bureau of the Census
Industry diversity	1408.794 (245.150)	0.401 (2.969)	Crain and Lee's (1999) diversity measure. It is the sum of the squared shares of Gross State Product originating in: agricultural services, mining, construction, manufacturing, transportation & utilities, wholesale and retail trade, FIRE, and services.	BEA
Government share of GSP	13.448 (2.899)	-0.339 (3.465)	Federal, state, and local government's share of GSP (share * 100)	BEA
Local government tax revenue share	36.825 (9.401)	-0.063 (6.451)	Local government tax revenue as a share of state and local tax revenue (share * 100)	Bureau of the Census, *Government Finances*
Intrastate banking indicator	0.700 (0.458)	--	=1 if the state permits intrastate branching through mergers and acquisitions, =0 otherwise	Kroszner and Strahan (1999)

Notes: Alaska, Hawaii and Washington D.C. are excluded. Descriptive statistics for variables in levels are over the period from 1977 to 2002, while the statistics for variables in first difference of logs are over the period from 1978 to 2002.

Table 2 – Spatial Estimates of U.S. State Income Growth

	(1) *OLS*	(2) *contiguity*	(3) *distance*	(4) *contiguity*	(5) *distance*	(6) *contiguity*	(7) *distance*
Constant	1.1255 ***	0.8305 ***	0.8219 ***	1.1116 ***	1.1232 ***	0.7491 ***	0.8384 ***
	(0.1455)	(0.1453)	(0.1440)	(0.1657)	(0.1659)	(0.1788)	(0.1740)
Labor	0.3207 ***	0.3052 ***	0.3074 ***	0.3220 ***	0.3182 ***	0.2948 ***	0.3083 ***
	(0.0945)	(0.0725)	(0.0705)	(0.0765)	(0.0741)	(0.0723)	(0.0708)
Education	-0.0062	-0.0051	-0.0056	-0.0033	-0.0050	-0.0058	-0.0055
	(0.0081)	(0.0089)	(0.0085)	(0.0088)	(0.0087)	(0.0090)	(0.0086)
Industry diversity	-0.1158 ***	-0.1131 ***	-0.1105 ***	-0.1120 ***	-0.1152 ***	-0.1116 ***	-0.1110 ***
	(0.0257)	(0.0186)	(0.0181)	(0.0181)	(0.0187)	(0.0188)	(0.0183)
Government share	-0.3270 ***	-0.3207 ***	-0.3086 ***	-0.3162 ***	-0.3195 ***	-0.3177 ***	-0.3097 ***
	(0.0266)	(0.0183)	(0.0179)	(0.0181)	(0.0185)	(0.0192)	(0.0189)
Local revenue tax share	-0.0217 ***	-0.0212 ***	-0.0208 ***	-0.0214 ***	-0.0218 ***	-0.0207 ***	-0.0209 ***
	(0.0077)	(0.0070)	(0.0068)	(0.0069)	(0.0070)	(0.0071)	(0.0069)
banking deregulation	0.1899	0.1978 *	0.1854	0.2179 *	0.1887	0.1874	0.1858
	(0.1198)	(0.1159)	(0.1144)	(0.1153)	(0.1212)	(0.1167)	(0.1136)
ρ		0.2243 ***	0.2356 ***			0.2933 ***	0.2223 ***
		(0.0329)	(0.0373)			(0.1040)	(0.0833)
λ				0.2357 ***	0.2429 ***	-0.0912	0.0197
				(0.0358)	(0.0402)	(0.1373)	(0.1069)
Sample size	1200	1200	1200	1200	1200	1200	1200
Adjusted R-squared	0.544						
AIC	3.9152	3.8801	3.8879	3.8829	3.8907	3.8814	3.8895
SC	3.9419	3.9183	3.9260	3.9210	3.9289	3.9238	3.9319
Log-likelihood		-2319.079	-2323.746	-2320.753	-2325.451	-2318.860	-2323.734

Notes: AIC and SC denote Akaike's Information Criterion and Schwarz Criterion. Significance levels are as follows: *** denotes the 1 percent level, ** denotes the 5 percent level, and * the 10 percent level. Standard errors are in parentheses. All of the variables entered the regression equations as first difference of logs except for banking deregulation. The dependent variable is the first difference of logged per capita income. See text for a description of the contiguity weights matrix and distance weights matrix. States included in Census regions and divisions are listed in the Appendix.

Table 3 – Spatial Estimates of U.S. State Income Growth by Region

	CENSUS REGIONS		*CENSUS DIVISIONS*	
	(1)	**(2)**	**(3)**	**(4)**
	contiguity	*distance*	*contiguity*	*distance*
Constant	0.8304 ***	0.8349 ***	0.8529 ***	0.9359 ***
	(0.1456)	(0.1450)	(0.1489)	(0.1458)
Labor	0.2976 ***	0.2955 ***	0.3178 ***	0.3207 ***
	(0.0723)	(0.0723)	(0.0725)	(0.0731)
Education	-0.0051	-0.0052	-0.0059	-0.0065
	(0.0086)	(0.0086)	(0.0087)	(0.0091)
Industry diversity	-0.1116 ***	-0.1120 ***	-0.1122 ***	-0.1141 ***
	(0.0185)	(0.0185)	(0.0186)	(0.0187)
Government share	-0.3154 ***	-0.3160 ***	-0.3149 ***	-0.3214 ***
	(0.0182)	(0.0182)	(0.0183)	(0.0184)
Local revenue tax share	-0.0214 ***	-0.0212 ***	-0.0196 ***	-0.0203 ***
	(0.0070)	(0.0071)	(0.0070)	(0.0071)
banking deregulation	0.1833	0.1856	0.2140 *	0.1970 *
	(0.1167)	(0.1151)	(0.1163)	(0.1190)
ρ_1 (Northeast)	0.2812 ***	0.2845 ***		
	(0.0639)	(0.0628)		
ρ_2 (Midwest)	0.1466 ***	0.1326 ***		
	(0.0508)	(0.0497)		
ρ_3 (South)	0.0940 ***	0.1073 ***		
	(0.0297)	(0.0295)		
ρ_4 (West)	0.1214 **	0.1060 **		
	(0.0533)	(0.0524)		
ρ_1 (New England)			0.2954 ***	0.2874 ***
			(0.0908)	(0.0933)
ρ_2 (Middle Atlantic)			0.3347 **	0.1001
			(0.1463)	(0.1569)
ρ_3 (East North Central)			0.4313 ***	0.2308 **
			(0.1068)	(0.1018)
ρ_4 (West North Central)			0.2446 ***	0.1888 ***
			(0.0540)	(0.0556)
ρ_5 (South Atlantic)			0.2321 ***	0.2354 ***
			(0.0772)	(0.0802)
ρ_6 (East South Central)			0.3334 ***	0.2114 **
			(0.1076)	(0.1075)
ρ_7 (West South Central)			-0.0883	-0.3137 **
			(0.1304)	(0.1357)
ρ_8 (Mountain)			-0.0065	-0.0236
			(0.0706)	(0.1300)
ρ_9 (Pacific)			0.0055	0.1381
			(0.1297)	(0.0967)
Sample size	1200	1200	1200	1200
AIC	3.8711	3.8717	3.8825	3.8961
SC	3.9220	3.9226	3.9546	3.9682
Log-likelihood	-2310.713	-2311.077	-2312.521	-2320.707

Notes: AIC and SC denote Akaike's Information Criterion and Schwarz Criterion. Significance levels are as follows: *** denotes the 1 percent level, ** denotes the 5 percent level, and * the 10 percent level. Standard errors are in parentheses. All of the variables entered the regression equations as first difference of logs except for banking deregulation. The dependent variable is the first difference of logged per capita income. See text for a description of the contiguity weights matrix and distance weights matrix. States included in Census regions and divisions are listed in the Appendix.

Table 4 – Spatial Correlation Coefficient Equality for Census Regions (p-values)

Contiguity Weights Matrix

	Northeast	Midwest	South	West
Northeast	--			
Midwest	**0.000**	--		
South	**0.000**	**0.000**	--	
West	**0.000**	**0.000**	0.123	--

Note: p-values are from joint significance t-tests on regional spatial coefficients from Column 1 of Table 3. Bold values identify pairs that are significantly different at the 10 percent level or better.

Inverse Distance Weights Matrix

	Northeast	Midwest	South	West
Northeast	--			
Midwest	**0.000**	--		
South	**0.000**	0.105	--	
West	**0.000**	**0.000**	0.477	--

Note: p-values are from joint significance t-tests on regional spatial coefficients from Column 2 of Table 3. Bold values identify pairs that are significantly different at the 10 percent level or better.

Table 5 – Spatial Correlation Coefficient Equality for Census Divisions (p-values)

Contiguity Weights Matrix

	New England	Mid Atlantic	East North Central	W. North Central	South Atlantic	East South Central	W. South Central	Mountain	Pacific
New England	--								
Mid Atlantic	0.240	--							
East North Central	**0.000**	**0.007**	--						
W. North Central	**0.083**	0.164	**0.000**	--					
South Atlantic	**0.000**	**0.068**	**0.000**	0.294	--				
East South Central	**0.011**	0.486	**0.000**	**0.049**	**0.000**	--			
W. South Central	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	--		
Mountain	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.086**	--	
Pacific	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.419	--

Note: p-values are from joint significance t-tests on regional spatial coefficients from Column 3 of Table 3. Bold values identify pairs that are significantly different at the 10 percent level or better.

Inverse Distance Weights Matrix

	New England	Mid Atlantic	East North Central	W. North Central	South Atlantic	East South Central	W. South Central	Mountain	Pacific
New England	--								
Mid Atlantic	**0.001**	--							
East North Central	**0.000**	**0.009**	--						
W. North Central	**0.005**	0.190	0.182	--					
South Atlantic	**0.000**	**0.039**	0.415	**0.029**	--				
East South Central	**0.000**	**0.012**	**0.000**	0.331	0.304	--			
W. South Central	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	--		
Mountain	**0.000**	**0.000**	**0.000**	**0.002**	**0.000**	**0.000**	**0.000**	--	
Pacific	**0.000**	0.264	**0.000**	0.108	**0.000**	**0.000**	**0.000**	**0.000**	--

Note: p-values are from joint significance t-tests on regional spatial coefficients from Column 4 of Table 3. Bold values identify pairs that are significantly different at the 10 percent level or better.

Appendix Table 1 – U.S. Bureau of the Census Regions and Divisions

States	***Division***	***Region***
CT, MA, ME, NH, RI, VT	New England	Northeast
NJ, NY, PA	Middle Atlantic	
IL, IN, MI, OH, WI	East North Central	Midwest
IA, KS, MN, MO, ND, NE, SD	West North Central	
DE, FL, GA, MD, NC, SC, VA, WV	South Atlantic	South
AL, KY, MS, TN	East South Central	
AR, LA, OK, TX	West South Central	
AZ, CO, ID, MT, NM, NV, UT, WY	Mountain	West
CA, OR, WA	Pacific	