Growth and Technological Leadership in US Industries: A Spatial Econometric Analysis at the State Level, 1963–1997

Valerien O. Pede[1], Raymond J.G.M. Florax[1,2], and Henri L.F. de Groot[2,3]

[1] Dept. of Agricultural Economics, Purdue University
403 W. State Street, West Lafayette, IN 47907–2056, USA
Phone: +1 (765) 494–4300, Fax: +1 (765) 494–9176
E-mail: vpede@purdue.edu, rflorax@purdue.edu

[2] Dept. of Spatial Economics, Vrije Universiteit
De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands
E-mail: hgroot@feweb.vu.nl

[3] Tinbergen Institute, Amsterdam, The Netherlands

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Abstract. For several decades, cross-country analyses have dominated the literature on economic growth. Recently, these analyses have been extended to include sectoral variation as well as spatial variation across sub-national regions. This paper investigates economic growth and potential determinants of the process of catch-up to technology leaders for several economic sectors, using data for the lower 48 US states from 1963 through 1997. We analyze the potential influence of factors such as human capital, and geographical distance to the technology leader. A spatially explicit growth model in which technological progress is endogenously determined is used to model productivity growth in nine US industries, ranging from mining to government, and including a combined sector of totals. The results indicate that none of the sectors exhibits σ-convergence, but they all show strong evidence of β-convergence with a convergence club pattern that is apparent for the wholesale/retail sector. The catch-up effect to the technology leader dominates the growth process in almost all sectors, and it works through the interaction with human capital.

Key words: regional economic growth, convergence, industry level, technological leadership, spatial econometrics
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1. Introduction

Economists have studied and debated economic growth and convergence for several decades now. Explaining disparities between regions and countries usually in terms of productivity levels has been at the center of the economic growth debate. Central to the investigation is whether productivity growth across countries or regions is converging (Dollar and Wolf 1993, Barro and Sala-i-Martin 1991, Rey and Montouri 1999, Islam 2003). The early tradition of research focusing on cross-country analyses is progressively being challenged by analyses at a lower level of spatial aggregation, such as counties in the US, or Nuts-2 regions in the European Union (EU). Typically, many of these studies use spatial econometric techniques, and focus on capturing the geographical dimension of growth and productivity convergence. In addition, a seminal contribution by Bernard and Jones (1996) initiated a discussion as to which sectors are driving the overall productivity convergence result (Sorensen 2001, Bernard and Jones 2001). This paper therefore focuses on the issue of space and technological leadership as determinants of economic growth, following up on earlier studies showing that geographical and technological distance to the technology leader has important implication in terms of productivity growth (Nelson and Phelps 1966, Benhabib and Spiegel 1994).

In the US, many studies have focused on states and Metropolitan Statistical Areas (MSA), and to some extent on counties in more recent years, as the spatial unit of observation. Meanwhile sectoral disaggregate studies of economic growth at these levels of spatial aggregation are few. Although technological leadership has been emphasized in cross-country analyses of economic growth, little is known about regional determinants of technology catch-up processes, and the extent to which "space" plays a role. It is largely unclear to what extent geographical and/or technological proximity to the technology leader impact growth and convergence. This paper therefore revisits the convergence debate for US industries, and extends previous studies by investigating economic growth and the process of catch-up to technology leaders for several economic sectors, using data for the lower 48 US states from 1963 through 1997.

The analysis starts with a standard convergence model that explores convergence patterns for different sectors in the lower 48 states, using well-known spatial econometric techniques. Next, a spatially explicit growth model in which technological progress is endogenously determined is applied to data for nine US industries, categorized as Mining, Construction, Manufacturing, Wholesale/Retail trade, Transportation and Utilities, Services, Finance Insurance and Real Estate, Government, and the combined sectors labeled Total.

The remainder of this paper is structured as follows. Section 2 reviews some of the recent literature on sectoral convergence of productivity, and technological leadership. Section 3 presents the spatial endogenous growth model, and discusses the estimation results. Section 4 provides a summary and some concluding notes.

2. Sectoral convergence of productivity levels

The economic growth literature devotes substantial attention to the study of economic growth or total factor productivity in a cross-country setting. Most studies focus on aggregate data for national economies, although a few utilize disaggregate levels. For instance, Dollar and Wolf (1993) examine the productivity growth in individual industries and the process of convergence of overall productivity growth for a set of developed countries. They observe that in 1963, the US led in labor productivity for all manufacturing industries, but over the period 1963–1986, labor productivity of the other countries converged to the US level in virtually every industry at different rates of convergence. Other studies concentrate on sectoral convergence within specific regions or countries. For instance, the European case is considered in various studies focusing on sectoral convergence at the regional level. Paci and Pigliarou (1997) fustigate the common tendency to overlook the importance of the continuous process of sectoral reallocation of resources that accompanies economic growth. They argue that aggregate convergence is largely a matter of structural change to the transitory shift from agriculture to manufacturing. In the same vein, Paci and Pigliarou (1999) also criticize the neglect of the role played by the sectoral mix and structural change on aggregate growth, claiming that sectors definitively matter in determining aggregate growth across European regions. Like the previous authors, Cuadrado-Roura et al. (1999) studied productivity convergence in Spain and emphasized the importance of a disaggregate analysis at a sectoral level. The authors argued that aggregate convergence seems to be due to the gradual homogenization of regional productive structures, and stressed the need for convergence analyses to be appropriately focused on sectors. More recently, Le Gallo and Dall'erba (2005) adopted a spatial approach to convergence and studied productivity convergence between European regions. They found variability between core and peripheral regions in terms of productivity and show that convergence speeds differ between sectors.

In the US, fewer studies have been done on sectoral convergence. In an early attempt, Barro and Sala-i-Martin (1991), investigate convergence across US states within eight non-agricultural industries using gross state products provided the Bureau of Economic Analysis (BEA) for the period 1963–1986. They found that convergence occurs at a similar rate in all industries except manufacturing, which converges at a faster rate than the other sectors. Similarly, Bernard and Jones (1996) employ cross-section and time series techniques to investigate convergence across US states and industries in terms of gross state product. Using a somewhat longer data series than Barro and Sala-i-Martin (1991), Bernard and Jones (1996) find that both cross-section and time series techniques provide evidence for convergence in manufacturing and mining sectors, but there is no evidence of convergence in construction and wholesale/retail sectors, while the results are mixed to negative for transportation and other services. Bernard and Jones (1996) point to differences in the data to reconcile the substantial difference of their results in comparison to those obtained by Barro and Sala-i-Martin (1991).

The unequal distribution of productivity levels is likely to a considerable extent due to disparities in technology levels. While some regions or countries are leading in technology, others are far behind. For example, Dollar and Wolf (1993) studied a sample of 13 industrialized countries and found that the US has maintained the lead in labor productivity for all manufacturing over the entire period 1963–1986. Also, the US has been recognized as technology leader in various industries in many studies. Dollar and Wolf (1993) show that other industrialized countries are converging to the US productivity level by way of catching up. They revealed that in the mid-1970s, Japan and Germany had achieved roughly 90% of the Total Factor Product (TFP) level of US manufacturing, and the difference among all OECD countries was small.

Convergence to the productivity level of the technology leader is largely determined by the technology available at the level of the follower. It is often argued that the stock of human capital plays a crucial role in the process of catching up to the technology leader. Nelson and Phelps (1966) postulated that the rate of adoption of a new technology depends on the ability of individuals or firms to implement new ideas and the gap between the theoretical level of technology, and the level of technology in practice. It can therefore be expected that economies located closer to a technology leader from geographical and technological standpoints may benefit more and grow faster. Benhabib and Spiegel (1994) extended Nelson and Phelps' idea by introducing the notions of domestic innovation and catch-up. They maintain that a country or region that lags behind the technology leader in terms of productivity but at the same time has a higher human capital stock will eventually catch up and overtake the leader.

It can be noticed from the above review that sectoral analysis of economic growth is relevant and the notions of space and technological leadership are important as well. These notions need to be taken into account when modeling the growth process. The present paper contributes to the literature by focusing on sectoral growth, space and technological leadership.

3. Exploratory analysis

The data used in the present paper are for the lower 48 states and the District of Columbia. Data on Gross Domestic Product (GDP) by states across industries are obtained from the Bureau of Economic Analysis (BEA). The annual GDP by state series consists of estimates through the period 1963–1997 for Standard Industrial Classification (SIC) industries.[1] Like Barro and Sala-i-Martin (1991) the present study focuses on eight standard non-agricultural sectors: Mining, Construction, Manufacturing, Transportation and Public Utilities, Wholesale and Retail Trade, Finance Insurance and Real Estate, Services, and Government. We also added a sector labeled Total, which represents the eight sectors combined. Individual state GDP deflators are unavailable, so we use the national GDP deflator to convert the nominal GDP into 1997 dollars.

The data on employment by sector are from the Bureau of Labor and Statistics (BLS). Our data represent a significant improvement over those used by Bernard and Jones

[1] GDP by state series are also available for 1997–2004 under the North American Industry Classification (NAICS). Conversion of the two series into a single series would have allowed us to cover a longer time period, but such a conversion is not feasible because the SIC and NAICS classifications are different in terms of constituent industries and aggregation.

(1992), and Barro and Sala-i-Martin (1991) for several reasons. The GDP data are from the most recent and updated estimate series from the BEA. According to Beemiller and Woodruff (2000) the state GDP data are revised and updated twice annually, with benchmark revisions occurring approximately every five years. Moreover, our study covers a longer time period than the previous two studies; 1963–1997 against 1963–1986 and 1963–1989 for Sala-i-Martin (1991) and Bernard and Jones (1996), respectively.

Educational data were obtained from the Economic Research Service (ERS) for the years 1970, 1980, 1990 and 2000. Human capital is defined as the average proportion over the 4 years for the population 25 years and older with at least a 4-year college degree.

There are no capital stock series available for US states by industries. Garofalo and Yamarik (2002) attempted to construct state-by-state capital stock and gross investment estimates using data on the service life and amount of capital equipment, and apportioning the national capital stock among the states. Due to data limitations for sectors, we follow a somewhat different approach to construct the state capital stock. For each sector, we constructed the series on the basis of the national capital stock data in constant 1997 prices (i.e., the stock of privately-owned and government-owned durable equipment and structures), which were allocated across states using wage and salary disbursements at the state level.

In order to account for the spatial typology of states, a weight matrix is used. The weight matrix defines the spatial connection between regions. Due to the typology of the US states, we consider that a distance-based weight matrix is most appropriate to capture potential spatial effects. We therefore define the spatial weight matrix on the basis of arc distances between the geographical midpoints of the states considered. It is a Boolean proximity matrix where elements are coded unity if the distance between states is less than 340.50 miles.[2]

Table 1 shows the average productivity level across the lower 48 states and the District of Columbia in each of the sectors, including the sectoral total, as well as the coefficient of variation expressed as a percentage. The mining sector is the most variable in term of productivity with coefficients of variation of 60% and 50% in 1963 and 1997, respectively. The Finance Insurance and Real Estate sector (hereafter FIRE) is by far the most productive sector with productivity levels of $128,474 in 1963, and $193,468 in 1997. The mining sector comes in second after FIRE in both years, respectively. While the variation in productivity level has decreased sharply for the mining sector between 1963 and 1997, and slightly for the government sector, it has increased for the other sectors with manufacturing showing the largest increase.

[Table 1 about here]

Table 2 shows the employment and output shares across sectors for the years 1963 and 1997. Comparing both years, the output share has increased in the FIRE and Services sectors, while it has declined in all other sectors. The same pattern is apparent for the employment share data.

[Table 2 about here]

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[2] The distance of 340.50 miles represents the minimum cutoff distance required to ensure that each state is linked to at least one other state.

Table 3 shows the average annual growth rate of state GDP per capita and its variation across sectors over the period 1963–1997. The highest average annual GDP growth rate in the sample is observed in the mining sector, while the wholesale/retail trade sector shows the lowest. The mining sector has more variability in the GDP growth rate as well.

[Table 3 about here]

Figure 1 shows the productivity level in each sector over the period 1963–1997. The general observation is that there is an upward trend of the productivity level in almost all sectors. The mining sector shows the most variability over the period.

[Figure 1 about here]

The top five most productive states in each sector in 1963 and 1997 are presented in Table 4. There is variability across industry and over time in terms of the productivity leader. For example, Kentucky was the most productive state in the manufacturing sector in 1963 but has been replaced by New Mexico in 1997. Only Louisiana and Wyoming lead the mining and transportation and utilities sectors respectively in both 1963 and 1997.

[Table 4 about here]

Figure 2 shows the coefficient of variation (yellow) of the states GDP per capita along with the Moran's I statistics (red) over the period 1963-1997. The coefficient of variation indicates the dispersion of productivity levels while the Moran's I statistic is a measure of spatial autocorrelation. In Figure 2, positive values of Moran's I are observed in all sectors, denoting that states with similar productivity levels are spatially clustered. However, the degree of spatial clustering varies between sectors. A persistent decline of Moran's I statistic is observed in the manufacturing and construction sectors from the early 1970. This is indicative of spatial defragmentation within these sectors over time, which may have been caused by similarity in term technology or geography. In the other sectors, the Moran's I statistic is rather stable or follows an irregular trend. The mining sector shows a good example of relatively stable Moran's I statistics over time, which may be explained by the fact that this industry is not footloose. The trend of the coefficient of variation of the states' GDP per capita is not similar across sectors either. A declining trend of the coefficient of variation denotes σ-convergence,[3] which suggests that the disparities of GDP per capita across states are becoming less pronounced. Figure 2 shows no real evidence of σ-convergence in any of the sectors considered. None of the sectors shows a steady decline of coefficient of variation over the period 1969–1997. However, a relatively stable GDP dispersion is observed in the construction and government sectors.

[Figure 2 about here]

4. Endogenous growth model with technological leadership

This section starts with the estimation of an unconditional convergence model in the tradition of Barro and Sala-i-Martin (1991) for each of the sectors. The unconditional growth

[3] The presence of β-convergence is a necessary although not a sufficient condition for the occurrence of σ-convergence (Barro and Sala-i-Martin 1995).

model expresses the growth rate of GDP per worker in each sector as a function of the initial GPD per worker in the same sector. It reads as:

$$\log\left[\frac{Y_{t+k}^{s}}{Y_{t}^{s}}\right] = \alpha + \beta \log\left(Y_{t}^{s}\right) + \varepsilon_{t}^{s}, \tag{1}$$

where Y_t^s is the initial GDP per worker, k the number of years in the sample period, s the different sectors. Results of the unconditional convergence models are presented in Table 5. In the unconditional convergence model, all the coefficients have the expected negative sign. This indicates that there is β-convergence in all sectors. The rate of convergence varies between 0.35% per year for the wholesale/retail trade sector and 4.02% for the manufacturing industry. The combined sector "Total" has a convergence rate of 1.67%, which is consistent with the prediction from cross-country and regional analyses (Abreu et al. 2005). The observed rate of convergence in the manufacturing sector is also consistent with the findings from Barro and Salai-Martin (1991).

[Table 5 about here]

In addition to the unconditional convergence estimation, we also test for the presence of convergence clubs within each sector. Following the traditional approach, we divide the sample into two groups based on the initial GDP per worker levels. We distinguish the groups of high initial GDP per worker and low initial GDP per worker states on the basis of above and below average GDP per worker in 1963. Following the "specific-to-general" approach, we estimated the unconditional convergence model using General Moments (GM) or Maximum Likelihood (ML) depending on the appropriate spatial process indicated by the LM tests of the OLS version of the model (Anselin and Rey 1991, Anselin and Florax 1995). Coefficients and variances are allowed to vary across groups and the Chow-Wald test is used to test the stability of coefficients across groups. The GM-HET is used to estimate the spatial error model while the ML-HET is used to estimate the spatial lag model.[4] Following Anselin and Rey (1991) we decided on the appropriate spatial process based on the LM test with the highest value.

Results presented in Table 5 indicate that the coefficient of initial GDP per worker is negative for both high and low GDP clubs in all sectors. The rate of convergence is typically higher for the low as compared to the high GDP club. This is consistent with the prediction from the neoclassical theory which stipulates that poor economies grow faster than richer ones. The Chow-Wald test of equality of coefficients across regimes is only significant for

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[4] With two regimes, the spatial error model reads as:

$$Y = \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \varepsilon \text{ , with } \varepsilon = \lambda W \varepsilon + \mu \text{ ,}$$

where $\varepsilon \sim (0, (I - \lambda W)^{-1} \Omega (I - \lambda W)^{-1})$. X_1 and X_2 are matrices of observations on the explanatory variables for each spatial regime, and Ω is the variance covariance matrix given by:

$$\begin{bmatrix} \sigma_1^2 I_1 & 0 \\ 0 & \sigma_2^2 I_2 \end{bmatrix},$$

where σ_1^2 and σ_2^2 are the variances corresponding to each regime.

The spatial lag model with regimes is given as follows:

$$Y = \rho WY + \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \varepsilon$$

Where ρ is a coefficient indicating the spatial correlation between the productivity level of a given state and its neighbors.

the FIRE and the wholesale/retail trade sectors. But since the absolute value of the coefficient of the initial GDP per capita is greater than one (in absolute value) for the low initial GDP group in the FIRE sector, the rate of convergence could not be calculated for this group.[5] Therefore, we admitted that the distribution of GDP per capita displays convergence clubs only in the wholesale/retail trade sector. This means that in the wholesale/retail trade sector, the rich and poor economies (states) exhibit different patterns of convergence.[6]

[Table 6 about here]

The unconditional growth specification is largely a descriptive tool, as it does not account for growth conditioning factors such as labor and capital inputs. Moreover, it takes technological progress as exogenously given, rather than explaining it in terms of factors that stimulate the growth of technology. We therefore continue by estimating an endogenous growth model. Our endogenous growth model is based on the initial idea of "domestic" effects of the human capital stock on economic growth, and the role of catching up to the technology leader as developed by Nelson and Phelps (1966), and Benhabib and Spiegel (1994). This model has formerly been applied in Pede et al. (2006) to investigate the pattern of economic growth in US counties over the period 1963–2003.

The model starts by a simple specification based on a Cobb-Douglas production function, which reads as:

5 When the coefficient of the initial GDP per capita is greater than one (in absolute value), it means that there is leapfrogging and the rate of convergence I undefined.

6 As a caution note, it should be pointed out that the Chow-Wald test may not be very powerful in detecting convergence clubs given that we only have 49 observations.

$$(\log Y_t^s - \log Y_0^s) = (\log A_t^s - \log A_0^s) + \alpha(\log K_t^s - \log K_0^s) + \beta(\log L_t^s - \log L_0^s) + (\log \varepsilon_t^s - \log \varepsilon_0^s), \quad (2)$$

where Y_t^s is GDP per worker, K_t^s physical capital, L_t^s labor, A_t^s the level of technology, ε_t^s an error term, and *s* represents the sectors.

Concisely, the Benhabib and Spiegel (1994) version of the model assumes that the level of technology can be explained by the level of human capital "domestically" and a catch-up term that depends on the distance to the technology leader in terms of GDP per capita, and the level of human capital that is available to adopt the ideas and technologies originating from the technology leader. In formal terms the level of technology is expressed as:

$$(\log A_t^s - \log A_0^s)_i = c + gH_i^s + mH_i^s \left[\frac{Y_{\max}^s - Y_i^s}{Y_i^s} \right], \quad (3)$$

where i (= 1, 2, …, n) indexes states, H refers to human capital available in the state, and $Y_{\max}$ refers to the state GDP per worker for the technology leader (i.e., the state with the highest productivity).[7] In a sense, Equation (3) can be seen as an a-spatial endogenous growth model which, after rearranging, reads as:

$$(\log A_t^s - \log A_0^s)_i = c + (g - m)H_i^s + mH_i^s \left[\frac{Y_{\max}^s}{Y_t^s} \right], \quad (4)$$

[7] For each sector, the state with the highest productivity level in the year 1997 is considered as technology leader. The top five most productive states in 1997 are presented in Table 4.

Equation (4) shows that the capacity for "domestic innovation" depends on the available human capital stock. The human capital stock independently enhances technological progress, and, holding human capital levels constant, states with lower initial productivity levels will experience a faster growth of total factor productivity (assuming both m and $g - m$ are positive).

The model presented in equation (4) is strictly topological invariant in the sense that changes in the size, shape and location of the areal units do not have a bearing upon the results. We therefore incorporate a spatial spillover effect in the available domestic human capital stock and a distance decay effect in the catch-up term, as follows:

$$(\log A_t - \log A_0)_i = c + gH_i + r \sum_{\substack{j=1 \\ j \in J_i(d)}}^{J} \frac{1}{d_{ij}} H_j + m \frac{H_i}{d_{i,\max}} \left[\frac{Y_{\max} - Y_i}{Y_i} \right], \qquad (5)$$

where states located within the 'cut-off distance' d are included in the $J_i(d)$ classes for the spatial spillover effect, $d_{i,max}$ represents the geographical distance of state i to the technology leader and r the coefficient of human capital accumulation in neighboring regions.

Rearranging and substitution gives:

$$(\log A_t - \log A_0)_i = c + gH_i - m \frac{1}{d_{i,\max}} H_i + r \sum_{\substack{j=1 \\ j \in J_i(d)}}^{J} \frac{1}{d_{ij}} H_j + m \frac{1}{d_{i,\max}} H_i \left(\frac{Y_{\max}}{Y_i} \right), \qquad (6)$$

Using OLS, we first estimate a model based on equation (2), where the technological progress is taken into account as in equation (6). For each sector, the previously defined weight matrix is used in the estimation of the spatial process. Estimation results are presented in Table 7 and summarized below.

[Table 7 about here]

In the "total" sector, the OLS estimation shows a positive Moran's I of errors significant at 1%. The Jarque-Bera test does not reject the assumption of normally distributed errors, and homoskedasticity of the errors is not rejected by the Breusch-Pagan test either. The LM tests indicate that the model should incorporate a spatially autoregressive process. We therefore estimated the spatial error model with regimes using GM estimator and allowing coefficients to vary across regimes. We distinguish two regimes, with high and low initial GDP levels, as before. Results of the estimation show a significant and positive effect of human capital in both poor and rich economies. The catch-up to the technology leader and physical capital show a strong positive effect on the productivity growth of the poor economies only. The productivity growth in the mining and FIRE sectors is mainly dominated by the catch-up effect. In the construction sector, the effect of physical capital is more prominent, with a stronger significance for the poor economies. Results are mixed with the transportation/utilities sector. A strong and significant effect of catch-up is observed for the poor economies while the spatial spillover effect and physical capital dominate for rich economies. As far as the service and wholesale/retail sectors are concerned, human capital dominates the productivity growth process for both rich and poor economies. In addition, the catch-up and the physical capital are strongly significant for poor economies. A strong and consistent catch-up effect is observed in the manufacturing sector.

Spillover of human capital and physical capital are also important for the poor economies only.

Overall, the catch-up effect seems to be an important determinant of productivity growth in almost all sectors. More especially, its effect is much stronger in the mining, FIRE, manufacturing and government than the other sectors. Moreover, poor economies seem to show stronger significance on the catch-up effect.

The results suggest three important notions. First, growth process are different whether aggregate or disaggregate data are considered. Results obtained for the total of all sectors differ from those obtained in the disaggregate sectors. Therefore, generalizing results for all sectors based on aggregate data may be misleading. Second, within the same sector the sign and magnitude of coefficients are not always consistent when distinctions are made between the low and high GDP states. This suggests that the determinants of the productivity growth process vary across economies (poor and rich). Third, the effects of human capital, and its domestic and spillover effects vary across sectors and results are mixed with regards to the sign of these factors. The negative coefficient on human capital, and its domestic and spillover effects in several sectors is unexpected. A priori, it was expected that human capital would be positively correlated with growth. Moreover, the domestic effect and the spillovers that accompany human capital should be expected to enhance GDP growth as well. Benhabib and Spiegel (1994) also observed a negative sign on the coefficient of human capital for a sample of countries in their study.

The estimated growth model seems to indicate that the catch-up with the technology leader dominates the growth process, mainly for the states that start-off with relatively low GDP levels. Indeed, the catch-up effect seems to be more consistent across sectors. It is positive in almost all sectors and more significant in the group of initially low GDP levels.

Benhabib and Spiegel (1994) also observed positive and significant effect of the catch-up. The further a state to the technology leader in terms of GDP per capita, the faster is its productivity growth. This justifies the strong dominance and significance of the catch-up term for the group of initially low GDP levels. With low GDP per capita at the beginning period, they converge faster to the technology leader. This is also consistent with prediction from neoclassical theory where poor economies are expected to grow faster. Due to the interaction between human capital and the catch-up term in the spatial Benhabib and Spiegel model, it could be concluded that the effect of human capital on growth is rather indirect, working through the catch-up term. Human capital by itself does not drive the growth process, but when interacted with the catch-up term its role becomes more prominent. Therefore, we could conclude that both geographic and technological proximity are relevant for the sectoral productivity growth. However, the technological effect is more prominent.

5. Conclusion

In this paper, we have utilized some exploratory and spatial econometric data analysis techniques to investigate issues of productivity growth, human capital, and technological leadership in US industries using SIC-based state level data from 1963 through 1997. For eight industries and the combined total we estimated a simple unconditional convergence model, an unconditional convergence model allowing for convergence clubs, and an endogenous growth model incorporating human capital and technological catch-up. Processes of σ-convergence were not detected in any of the sectors, but all sectors show strong evidence of β-convergence. Only the wholesale/retail sector exhibits pattern of convergence clubs with low and high initial GDP states showing different rates of β-convergence across groups. With regard to the endogenous growth model, results are mixed for the effects of human capital, and its spillover and domestic effects. However, the catch-up to the technology leader shows more consistency across sectors. It is not so much human capital that dominates the sectoral growth process but rather the induced effect through catch-up with the technology leader. The catch-up effect consistently drives the growth process in almost all sectors. In particular, the states with initially low levels of GDP show more pronounced catch-up effects. The effect of human capital is indirect, working through the interaction with the catch-up term to drive the growth process. Geographic and technological proximity are both relevant for the sectoral productivity growth. However, the technological effect seems to be more prominent. Further improvement regarding models and data could help to substantiate our conclusion. As far as models improvement are concerned, possible consideration for future studies could be: system approach estimation, panel data set up and higher order models accounting for both technological and sectoral spillover effects.

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Table 1: Productivity Levels and Variation across States.

Sectors	1963 Average	1963 Coefficient of Variation (%)	1997 Average	1997 Coefficient of Variation (%)
Mining	71641	60	134022	50
Construction	40822	16	57800	17
Manufacturing	40344	23	76173	29
Transportation and Public Utility	61941	11	105626	14
Wholesale Trade/ Retail trade	35602	9	41565	13
F.I.R.E	128474	20	192468	25
Service	32900	14	42534	17
Government	33321	18	48331	17
Total	43574	13	61755	15

Table 2: Output and Employment Shares across States.

Sectors	Output Shares 1963	Output Shares 1997	Employment Shares 1963	Employment Shares 1997
Mining	2.3	1.5	1.1	0.5
Construction	4.9	4.2	5.2	4.6
Manufacturing	28.3	17.6	30.2	15.3
Transportation and Public Utility	9.4	8.5	6.9	5.2
Wholesale Trade/ Retail trade	17.4	16.0	20.8	23.3
F.I.R.E	14.6	19.2	5.0	5.8
Service	10.9	20.7	14.3	29.1
Government	12.3	12.3	16.5	16.2
Total	100	100	100	100

Table 3: Average Annual Growth Rate and Variation across States (percent), 1963–1997.

Sectors	All States Average	All States Coefficient of Variation
Mining	3.33	57
Construction	1.10	47
Manufacturing	2.04	51
Transportation and Public Utility	1.65	28
Wholesale Trade/ Retail trade	0.47	61
F.I.R.E	1.30	56
Service	0.77	57
Government	1.14	32
Total	1.05	38

Table 4: Top Five most Productive States by Industry.

		Rank				
Sectors	Years	1	2	3	4	5
Mining	1963	Louisiana	Wyoming	North Dakota	California	Texas
	1997	Louisiana	California	Texas	New Mexico	Wyoming
Construction	1963	Connecticut	Illinois	California	Washington	Oregon
	1997	Rhode Island	Massachusetts	New Jersey	Connecticut	Nevada
Manufacturing	1963	Kentucky	Michigan	Delaware	Nevada	West Virginia
	1997	New Mexico	Louisiana	Oregon	Wyoming	District of Columbia
Transportation and Public Utility	1963	Wyoming	Arizona	Mississippi	Nevada	District of Columbia
	1997	Wyoming	District of Columbia	Rhode Island	Texas	New York
Wholesale Trade/ Retail trade	1963	California	Washington	New York	Nevada	Michigan
	1997	New Jersey	Connecticut	California	New York	Washington
F.I.R.E	1963	Nevada	Delaware	New Mexico	California	New Jersey
	1997	Connecticut	New York	California	New Jersey	Rhode Island
Services	1963	Nevada	California	Wyoming	Michigan	New Mexico
	1997	District of Columbia	California	Connecticut	New Jersey	Washington
Government	1963	Virginia	Maryland	Rhode Island	Washington	California
	1997	District of Columbia	Virginia	Maryland	Nevada	Washington
Total	1963	Wyoming	Nevada	Michigan	California	Washington
	1997	Connecticut	New York	Delaware	District of Columbia	New Jersey

Table 5: Unconditional Convergence Model.

Sectors	Beta	Standard Error	Rate of Convergence
Mining	-0.3810***	0.0954	1.41
Construction	-0.5334***	0.1248	2.24
Manufacturing	-0.7447***	0.1441	4.02
Transportation and Public Utility	-0.6996***	0.1785	3.54
Wholesale Trade/Retail trade	-0.1125	0.1577	0.35
F.I.R.E	-0.5794***	0.1548	2.55
Services	-0.3386**	0.1588	1.22
Government	-0.3546***	0.0907	1.29
Total	-0.4333***	0.1427	1.67

Significance at the 1 and 5 level is signaled by *** and ** , respectively.

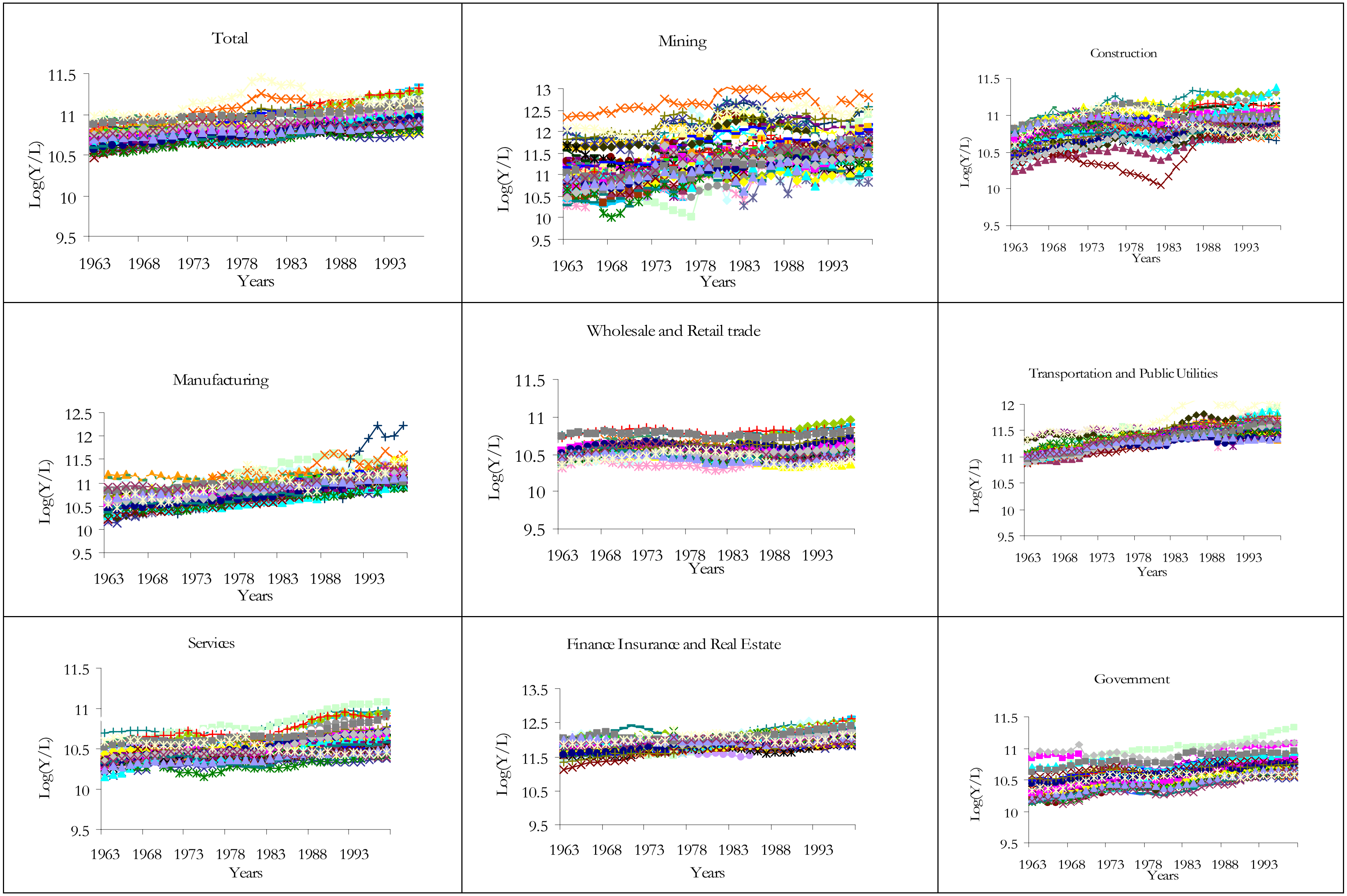

Figure 1: Logarithm of State Productivity Levels by Sector, 1963–1997.

Figure 2: Coefficient of Variation and Moran’s I of Productivity Levels, 1963–1997.

Table 6: Unconditional Convergence with Spatial Regimes, 1963–1997.

Sectors	Total			Mining			Construction		
Models [a]	OLS	GM-HET		OLS	GM-HET		OLS	ML-HET	
		Low	High		Low	High		Low	High
Variables									
Constant	4.97***	7.58***	2.45	4.87***	7.68***	5.02***	6.00***	9.08***	5.12
Log GDP 1963	-0.43***	-0.64***	-0.19	-0.38***	-0.64***	-0.40***	-0.53***	-0.83***	-0.46
Lagged GDP growth								0.25**	
Spatial AR[b]		0.54***			0.49				
Convergence rate[c]	1.67	2.92	0.6	1.37	2.92	1.46	2.16	5.06	1.76
R^2 adjusted	0.14			0.23			0.26		
AIC	-62.82			31.91			-46.86	-46.6	
LIK	33.4			-13.95			25.43	28.3	
JB[d]	5.06			1.88			5		
BP[e]	0.05			0.14			0.91		
Chow-Wald[f]		1.91			0.71			3.02	
I	0.42***			0.24***			0.09		
LM-error	16.6***			5.58***			0.81		
Robust LM-error	0.64			8.08***			0.11		
LM-lag	16.28***			1.75			1.27		
Robust LM-lag	0.32			4.26***			0.57		
LM-SARMA	16.92***			9.84***			1.38		

[a] Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively.
[b] Spatial Autoregressive parameter of the spatial error model.
[c] In percentage points per year. The convergence rate equals $100 \times (\ln(b+1))/-T$, where b is the estimated coefficient for the GDP per capita level in 1963, and T the length of the 1963–1997 time period.
[d] Jarque Bera test for normality of the errors.
[e] Breusch-Pagan test with random coefficients as the alternative hypothesis.
[f] Chow-Wald test for stability of coefficients across regimes.

Table 6: Unconditional Convergence with Spatial Regimes, 1963–1997 (continued).

Sectors	Transportation/Utilities			Services			Finance Insurance and Real Estate		
Models [a]	OLS	ML-HET		OLS	GM-HET		OLS	GM-HET	
		Low	High		Low	High		Low	High
Variables									
Constant	8.25***	12.33***	5.82	3.77***	5.93**	8.92***	7.20***	13.78***	3.86
Log GDP 1963	-0.70***	-1.07***	-0.48	-0.33***	-0.55**	-0.82***	-0.58***	-1.15***	-0.31
Lagged GDP growth		0.37***							
Spatial AR[b]					0.05***			0.63***	
Convergence rate[c]	3.44	IND[g]	1.87	1.14	2.28	4.90	2.48	IND	1.06
R^2 adjusted	0.23			0.07			0.21		
AIC	-55.87			-50.11			-6.89		
LIK	29.93			27.05			5.44		
JB[d]	3.60			1.50			3.09		
BP[e]	5.06			3.68			0.00		
Chow-Wald[f]		1.93			3.55			5.85***	
I	0.23***			0.14**			0.48***		
LM-error	4.62**			1.75			21.82***		
Robust LM-error	0.98			0.28			10.31***		
LM-lag	8.10***			1.50			13.70***		
Robust LM-lag	4.45**			0.02			2.20		
LM-SARMA	9.07***			1.78			24.01***		

[a] Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively.
[b] Spatial Autoregressive parameter of the spatial error model.
[c] In percentage points per year. The convergence rate equals $100 \times (\ln(b+1))/-T$, where b is the estimated coefficient for the GDP per capita level in 1963, and T the length of the 1963–1997 time period.
[d] Jarque Bera test for normality of the errors.
[e] Breusch-Pagan test with random coefficients as the alternative hypothesis.
[f] Chow-Wald test for stability of coefficients across regimes.
[g] IND means the convergence rate could not be calculated because the estimated coefficient of the initial GDP per capita (in absolute value) is greater than one.

Table 6: Unconditional Convergence with Spatial Regimes, 1963–1997 (continued).

Sectors	Wholesale/Retail Trade			Manufacturing			Government		
Models[a]	OLS	GM-HET		OLS	ML-HET		OLS	GM-HET	
		Low	High		Low	High		Low	High
Variables									
Constant	1.33	10.03***	2.27	8.51***	6.63*	11.14***	4.06***	6.64***	5.31**
Log GDP 1963	-0.11	-0.95***	-0.19	-0.74***	-0.55	-0.98***	-0.35***	-0.60***	-0.47***
Lagged GDP growth					-0.24				
Spatial AR[b]		0.32***						0.24***	
Convergence rate[c]	0.33	8.56	0.60	3.85			1.25	2.62	1.81
R^2 adjusted	0.01			0.35			0.23		
AIC	-86.74			-6.85			-75.53		
LIK	45.37			5.42			39.77		
JB[d]	5.86**			221.46***			227.76***		
BP[e]	0.38			1.15			0.04		
Chow-Wald[f]		5.80***			1.29			1.71	
I	0.15***			-0.08			0.12*		
LM-error	2.23			0.58			1.27		
Robust LM-error	0.07			0.34			4.22**		
LM-lag	2.18			1.33			0.12		
Robust LM-lag	0.02			1.08			3.07*		
LM-SARMA	2.24			1.67			4.33*		

[a] Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively.
[b] Spatial Autoregressive parameter of the spatial error model.
[c] In percentage points per year. The convergence rate equals $100 \times (\ln(b+1))/-T$, where b is the estimated coefficient for the GDP per capita level in 1963, and T the length of the 1963–1997 time period.
[d] Jarque Bera test for normality of the errors.
[e] Breusch-Pagan test with random coefficients as the alternative hypothesis.
[f] Chow-Wald test for stability of coefficients across regimes.

Table 7. Endogenous Growth Model with Diagnostics for Spatial Models.

Sectors	Total			Mining			Construction		
Models [a]	OLS	GM-HET		OLS	GM-HET		OLS	GM-HET	
		Low	High		Low	High		Low	High
Variables									
Constant	-0.270***	-0.318**	-0.134	-0.052	1.280	-0.506	-0.250	-0.178	-0.303
Human capital	0.012***	0.017***	0.014***	-0.031	-0.036	-0.020	-0.003	-0.012	0.005
Spillover human capital	0.007	0.007	0.003	0.022	-0.015	0.041	0.012	0.010	0.015
Spatial domestic effect	-0.009	-0.037**	-0.003	0.052***	-0.007	0.017	-0.010	0.009	-0.032
Catch-up	0.011***	0.024***	0.009	0.012***	0.014***	0.028**	0.010	0.004	0.030
Log labor ratio	-0.880***	-1.087***	-0.436	1.082	0.022	-0.347	-1.464***	-1.282**	-0.956*
Log capital ratio	0.421***	0.516***	0.177	-0.516	-0.170	0.013	0.732***	0.672***	0.477*
Spatial AR parameter[b]		0.325***			0.460***			-0.440***	
R^2 adjusted	0.76			0.36			0.48		
AIC	-121.23			28.01			-59.51		
LIK	67.61			-7.00			36.75		
JB[c]	1.03			3.79			9.93***		
BP[d]	8.42			4.35			9.93		
Chow-Wald[e]		7.91			4.52			4.67	
I	0.17***			0.12**			0.10*		
LM-error	2.56*			1.38			0.73		
Robust LM-error	1.71			2.47			2.51		
LM-lag	1.10			0.28			0.01		
Robust LM-lag	0.25			1.38			1.78		
LM-SARMA	2.81			2.76			2.51		

[a] Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively.
[b] Spatial Autoregressive parameter of the spatial error model.
[c] Jarque Bera test for normality of the errors.
[d] Breusch-Pagan test with random coefficients as the alternative hypothesis.
[e] Chow-Wald test for stability of coefficients across regimes.

Table 7. Endogenous Growth Model with Diagnostics for Spatial Models (continued).

Sectors	Transportation/Utilities			Services			Finance Insurance and Real Estate		
Models [a]	OLS	GM-HET		OLS	GM-HET		OLS	GM-HET	
		Low	High		Low	High		Low	High
Variables									
Constant	-0.169	0.25	-0.197	-0.197	0.080	-0.465	-0.400*	-0.367	-0.587
Human capital	0.008	0.012	0.002	0.027***	0.012*	0.046***	0.010	-0.010	0.031***
Spillover human capital	0.020***	0.015	0.021***	-0.011*	-0.024***	-0.022**	0.001	0.009	0.007
Spatial domestic effect	-0.028*	-0.140**	0.002	-0.027***	-0.046***	0.029	-0.008	-0.015	-0.025
Catch-up	0.025**	0.090**	0.005	0.019***	0.039***	-0.019	0.021***	0.032***	0.025**
Log labor ratio	-0.880***	0.039	-1.105***	-0.653***	-0.740***	-0.563	-0.791*	-0.426	-0.804
Log capital ratio	0.391***	-0.033	0.490***	0.303***	0.329***	0.303	0.432**	0.311*	0.345
Spatial AR parameter		-0.140***			0.120***			0.400***	
R^2 adjusted[c]	0.48			0.66			0.69		
AIC	-70.57			-95.10			-48.80		
LIK	42.29			54.55			31.40		
JB	2.32			0.16			5.03*		
BP[d]	7.87			8.80			13.96**		
Chow-Wald[e]		9.17			16.41**			19.68***	
I	-0.05			0.04			0.22***		
LM-error	0.27			0.18			3.78**		
Robust LM-error	0.50			0.18			2.60*		
LM-lag	0.04			0.06			1.55		
Robust LM-lag	0.28			0.06			0.37		
LM-SARMA	0.56			0.24			4.15		

[a] Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively.
[b] Spatial Autoregressive parameter of the spatial error model.
[c] Jarque Bera test of normality of errors.
[d] Breusch-Pagan test with random coefficients as the alternative hypothesis.
[e] Chow-Wald test for stability of coefficients across regimes.

Table 7. Endogenous Growth Model with Diagnostics for Spatial Models (continued).

Sectors	Manufacturing			Wholesale/Retail Trade			Government		
Models [a]	OLS	ML-HET		OLS	GM-HET		OLS	GM-HET	
		Low	High		Low	High		Low	High
Variables									
Constant	-0.459***	-1.660***	0.332	-0.200*	-0.252**	-0.280	0.170	0.066	0.331
Human capital	-0.012	-0.001	-0.002	0.010**	0.020***	0.006	0.036	0.018	-0.046
Spillover human capital	0.042***	0.058***	0.014	-0.004	-0.006	0.001	-0.002	0.001	-0.007
Spatial domestic effect	-0.048**	-0.032**	-0.114***	0.007	-0.058***	-0.001	-0.046	-0.046**	0.032
Catch-up	0.046***	0.055***	0.070***	-0.002	0.033***	0.016	0.015***	0.02***	0.02***
Log labor ratio	-0.829*	-1.711***	-0.569	-0.593***	-1.005***	-0.195	-0.157	-0.649**	0.179
Log capital ratio	0.386*	0.935***	0.260	0.310***	0.502***	0.135	0.045	0.330**	-0.137
Spatial AR parameter					0.156***			0.400***	
Lagged GDP growth		-0.180							
R^2 adjusted[c]	0.60			0.45			0.41		
AIC	-26.17			-112.11			-83.79		
LIK	20.08			63.05			48.90		
JB	3.81			3.83			3.07		
BP[d]	14.56**			16.54***			20.57***		
Chow-Wald[e]		60.81***			35.01***			13.68**	
I	-0.08			0.07			0.19***		
LM-error	0.65			0.35			3.02*		
Robust LM-error	2.77*			3.86**			10.47***		
LM-lag	4.25**			0.06			0.076		
Robust LM-lag	6.36**			3.58***			7.53***		
LM-SARMA	7.02**			3.94			10.55***		

[a] Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively.
[b] Spatial Autoregressive parameter of the spatial error model.
[c] Jarque Bera test for normality of the errors.
[d] Breusch-Pagan test with random coefficients as the alternative hypothesis.
[e] Chow-Wald test for stability of coefficients across regimes.