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A Spatial Investigation of σ-Convergence in China

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A Spatial Investigation of σ-Convergence in China

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Abstract

Using techniques of spatial econometrics, this paper investigates σ-convergence of provincial real per capita gross domestic product (GDP) in China. The empirical evidence concludes that spatial dependence across regions is strong enough to distort the traditional measure of σ-convergence. This study focuses on the variation of per capita GDP that is dependent on the development processes of neighboring provinces and cities. This refinement of the conditional σ-convergence model specification allows for analysis of spatial dependence in the mean and variance. The corrected measure of σ-convergence in China indicates a lower level of dispersion in the economic development process. This implies a smaller divergence in real per capita GDP, although convergence across regions is still a challenging goal to achieve in the 2000s.

Keyword: σ-convergence, Moran's index, spatial dependence, spatial lag.

JEL Classification: C23, O18, O53, R11

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1 Introduction

Sigma (σ) convergence is a classic measurement of regional disparity (of real per capita GDP, income, or employment, etc.). It is the least complex measure of income inequality. σ-convergence is a phenomenon of decreasing dispersion of real per capita GDP or income (in logarithmic form) across regions over time. An alternative to σ-convergence is the β-convergence model. The β-convergence model gauges the negative partial correlation between growth in GDP and its initial level. Therefore, the less developed regions would tend to grow faster than the developed areas, leading to eventual equality (see Barro and Sala-i-Martin [1995], Sala-i-Martin [1996] for more details). Among ever growing country studies of growth convergence, there are several papers, both in English and Chinese, on the growth experience of the Chinese economy (see Chen and Fleisher [1996], Lin and Liu [2003] and references cited there).

The traditional use of σ- or β-convergence in most empirical applications does not explicitly consider spatial heterogeneity or spatial dependence. However, the convergence is calculated from a set of heterogeneous cross section units. Most findings of the non-convergence of dispersion in real per capita GDP or income in China and other countries may be due to model misspecification. This misspecification includes spatial dependence, time series correlation or data nonstationarity in general. From a spatial econometric perspective, Rey and Montouri [1999] examined the β-convergence in regional income for the U. S. economy. LeSage [1999] and Ying [2003] offered exploratory spatial analyses of β-convergence in China based on the provincial GDP growth.

The relationship between σ- and β-convergence is controversial (Friedman [1992], Quah [1993]). The general consensus is that β-convergence does not necessarily imply σ-convergence. However, β-convergence could be derived from σ-convergence (see also Bernard and Jones [1996]). Because of standard deviation's simple formulation, both Friedman [1992] and Quah [1993] called for more direct investigation of σ-convergence. Further, the spatial analysis of σ-convergence is still an unexplored territory.

The spatial dependence of cross section units may vary over time and this changes the measure of σ-convergence. The time path of σ-convergence is typically used to study the development process of a nation. Without considering the effects of spatial dynamics, the traditional measure of σ-convergence may be biased and misleading. Rey and Dev [2004] address the issue of σ-convergence in the presence of spatial effects. The focus of this paper is the measure of σ-convergence with spatial dynamics. Using methods of spatial econometrics (Anselin[1988]), we investigate spatial dependence in the mean and in the variance. The mean process is a spatial lag model. The variance process is analyzed using a generalized autoregressive conditional heteroscedasticity (GARCH) specification (Engle [1982], Bollerslev [1986]) for the spatial data. This is a novel approach to measure the regional decomposition of σ-convergence.

Section 2 reviews the concept and definition of σ-convergence. Based on the Chinese real per capita GDP, preliminary data analysis for spatial heterogeneity and dependence across 30 provinces and cities over 27 years is presented. In Section 3, we formalize the model of spatial dependence in the mean and in the variance. Section 4 outlines the quasi-maximum likelihood estimation (QMLE), and presents the empirical results of real per capita GDP in China. Our analysis of conditional σ-convergence indicates a lower level of dispersion in real per capita GDP but not necessary the convergence. The provinces and cities located in the east have begun to prosper, while central and west regions struggle to catch up. The developmental goal toward income equality or convergence across regions is challenging. The last section concludes.

2 σ-convergence

Let Y_{it} be the variable of interest in measuring the development of region i at time t (i = 1,2…,N; t = 1,2,…,T). Denote the logarithm $y_{it} = ln(Y_{it})$, and $\bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_{it}$ the regional average at time t. Then, the standard deviation of y_{it} for a nation composed of N regions at time t is defined by:

$$s_t = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(y_{it} - \bar{y}_t\right)^2}$$

If s_t is decreasing over time, then the national development process is considered *σ-convergent*. The convergence process of standard deviation or s_t indicates the eventual equality or parity of the regional growth and development process. Equivalently, for each time period t, s_t can be expressed as the estimated standard error of the constant (across regions) regression model as follows:

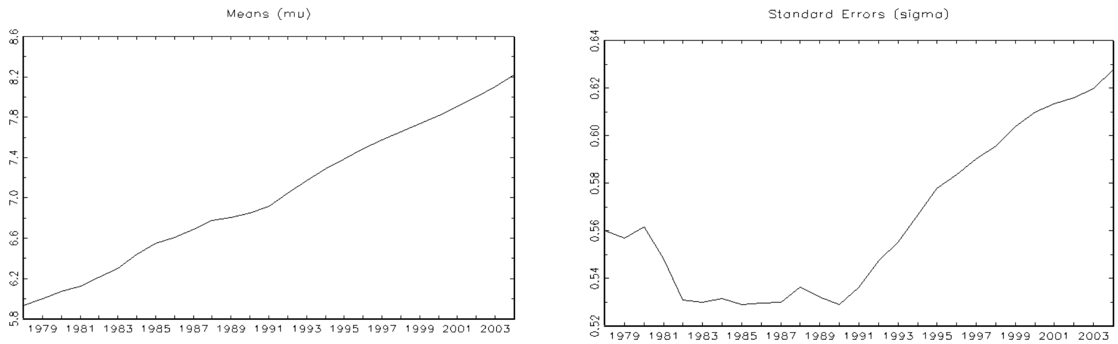
$$y_{it} = \mu_t + \varepsilon_{it} \qquad (2.1)$$

For simplicity, we first assume that the model error ε_{it} is independently distributed with zero mean and variance σ_t^2. The estimated model is $y_{it} = \bar{y}_t + e_{it}$ where e_{it} is the residual and s_t is the sample estimate of σ_t. The important question is whether the variable y_{it} is free of spatial dependence. In other words, for a given time t, is the assumed constant estimate of standard error σ_t or s_t consistent with the heterogeneous spatial (cross section) data involved?

Using panel data of logged real per capita GDP across 30 provinces and cities (henceforth, "states")[1] in China, Figure 1 plots the time series estimates of the mean (left panel) and standard error (right panel) from 1978 to 2004. It is clear that the cross section mean of logged real per capita GDP increased over time, and the standard error decreased first until 1990, then increased thereafter. Without considering the spatial correlation or dependence across states, there is a clear pattern of a divergent process in the standard errors since 1990.

[1] The 30 cross section units or states are based on the administrative division of China. Panel data series on per capita GDP across these 30 states over 27 years from 1978 to 2004 are obtained from various years of Statistical Yearbook of China. The latest data of Chongqing city is included in Sichuan province. For spatial analysis, the "island" Hainan is assumed to be "connected" with the nearest inland Guangdong province. See Appendix Table A.1 for the complete list of states as well as their regional and GDP level classifications.

Figure 1: Mean and Standard Error of Logged Real Per Capita GDP:
1978 - 2004



3 Spatial Dependence

In the literature of spatial econometrics (Anselin [1988]), Moran's Index I is used to study the spatial dependence of $y_{it} = ln(Y_{it})$. From the constant regression equation (2.1), $\varepsilon_{it} = y_{it} - \mu_t$ and ε_{it} is assumed to be normally distributed with zero mean and constant variance σ_t^2. Let $\varepsilon_t = [\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{Nt}]'$. The Moran's Index for time t is defined by:

$$I_t = \frac{\varepsilon_t' W \varepsilon_t}{\varepsilon_t' \varepsilon_t} \qquad (3.1)$$

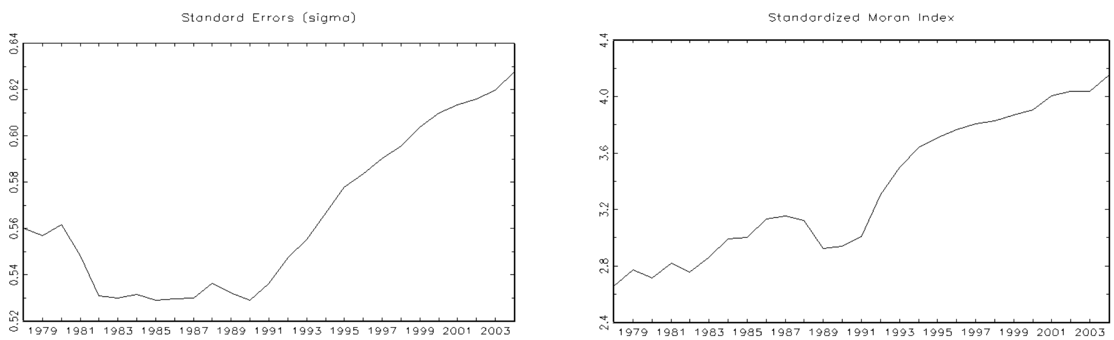
The sample estimate of I_t is obtained by replacing the residual $e_{it} = y_{it} - \bar{y}_t$ for ε_{it}. We note that W is an N by N, row-standardized, zero-diagonal, spatial weight matrix. For simplicity, we assume W is a time independent, location-based, binary-contiguity, weight matrix, with value 1 for the adjacent neighbors and 0 otherwise[2].

[2] Anselin [1988] provides detailed discussions of defining and using various forms of spatial weight matrix to study the spatial dependence in cross section data. A more realistic but subjective alternative is to weight neighbors differently with their economic influence such as output, consumption, or employment. For example, using GDP level Y_{it} to construct the economic weights as $W^* = W.*E$ where the element of E matrix is defined by: $E_{ij} = \frac{1}{\left|\bar{Y}_i - \bar{Y}_j\right|}$ and $\bar{Y}_i = \frac{1}{T}\sum_{t=1}^{T} Y_{it}$ is the i-th state average of Y_{it} over time. The notation ".*" means the element-by-element multiplication of matrices.

The standardized I_t is normally distributed, and it is used to test the significance of spatial dependence across regions. In addition, Lagrangian Multiplier tests are available for testing the specific structure of spatial dependence (see Anselin [1988], Anselin, Bera, Florax and Yoon [1996], Anselin and Rey [1991])[3].

In Figure 2 below, the time varying plot of the standard error s_t (left panel) is compared with the corresponding Moran's indices I_t (right panel). I_t varies over time, and resembles the increasing trend of s_t, particularly, after 1990. From that period on, the structure of spatial dependence changed. We suspect that the divergence of standard deviations may be caused by the increasing spatial dependence across states from the early 1990s. Without incorporating the spatial correlation or dependence, the measure of σ-convergence (that is, estimated standard error) may be misleading.

Figure 2: Standard Errors and Standardized Moran's Index of Logged Real Per Capita GDP: 1978 - 2004



Appendix Table A.2 lists the estimated mean, standard error, and standardized Moran's index from the constant regressions. In addition, the p-values of Moran's index are reported. These p-values indicate the significance of the spatial dependence across states for all years.

[3] These well-known tests were designed for testing the model specification of spatial dependence. But they are limited for diagnostic checking of an estimated spatial model. Anselin and Keleijian [1997] extended the Moran's I test procedure for spatial error correlation in the presence of spatially lagged dependent variables. The asymptotic properties of this test statistic were studied for several applications, including a spatial lag model, by Keleijian and Prucha [2001]. However, this test procedure is derived based on the estimation method with instrumental variables.

3.1 Higher Orders of Spatial Dependence

So far, we have considered the *first-order* spatial dependence based on the contiguity spatial weight matrix W. Higher orders of spatial weight matrices (that is, "neighbors' neighbors") can be formally constructed by taking the power of the first-order contiguity weight matrix W with redundant and circular elements removed (see Anselin [1988]). Therefore, similar to time series analysis of autocorrelation and partial autocorrelation functions, these matrices can be applied to study the spatial dependence at higher orders. In particular, the *spatial autocorrelation coefficients* ϕ_{kt} (for order k at time t) are estimated from:

$$y_t = \alpha_t + \phi_{kt} W_k y_t + \varepsilon_t, \quad k = 1,2,... \qquad (3.2)$$

Where, W_k is the k-th order of contiguity spatial weight matrix as described above. Similarly, the *spatial partial autocorrelation coefficients* are calculated as the estimated coefficient ρ_{kt} for the last (k-th) lag from the regression:

$$y_t = \alpha_t + \rho_{1t} W_1 y_t + \rho_{2t} W_2 y_t + \cdots + \rho_{kt} W_k y_t + \varepsilon_t, \quad k = 1,2,... \qquad (3.3)$$

The estimated spatial autocorrelation coefficients ϕ_{kt} and spatial partial autocorrelation coefficients ρ_{kt} with their corresponding estimated standard error are the basis for model specification. Identification of the proper order of spatial dependence is arrived at by the same methodology as time series analysis for model identification.

For spatial analysis, a sparse matrix computation may be required for a large dimension of spatial weight matrix W. In the Appendix, Table A.3 and A.4 report the estimates of spatial autocorrelation and partial autocorrelation coefficients up to the 5-th order of spatial dependence, respectively. Although the highest order for the Chinese contiguity weight matrix is "6", only one link (Shanghai and Xinjiang) is left in W_6. The next highest order "5" is used. These regression results confirm that only the first spatial lag is required to specify the spatial dependence of real per capita GDP in China. Therefore, we assume the first-order, spatial lag model for the Chinese real per capita GDP specification. Further analysis of spatial dependence can then be divided into two parts.

3.2 Spatial Dependence in the Mean

Let $y_t = [y_{1t}, y_{2t}, \ldots, y_{Nt}]'$. A spatial lag model of the first order is defined by:

$$y_t = \alpha_t + \rho_t W y_t + \varepsilon_t \qquad (3.4)$$

Equivalently, we write the first order spatial dependent process for the mean μ_{it} as follows:

$$y_{it} = \mu_{it} + \varepsilon_{it}$$
$$\mu_{it} = \alpha_t + \rho_t \sum_{j=1, j\neq i}^{N} W_{j.} y_t$$

Where, $W_{j.}$ is the j-th row of spatial weight matrix W. Therefore μ_{it} varies across state i for time t. The variation of μ_{it} over i comes from the effect of spatial dependence.

3.3 Spatial Dependence in the Variance

It is possible to describe the spatial dependence in the variance similar to that in the mean process. Denote σ_{it}^2 as the state and time-varying variance, and $\sigma_t^2 = [\sigma_{1t}^2, \sigma_{2t}^2, \ldots, \sigma_{Nt}^2]'$ is the vector of heterogeneous variances across states for time t. We further assume that the standardized error $u_{it} = \varepsilon_{it}/\sigma_{it}$ follows a standardized normal distribution.

Conditional to the neighboring states' variances and squared error, the variance process is defined by:

$$\sigma_t^2 = \varsigma_t + \gamma_t W \varepsilon_t^2 + \delta_t W \sigma_t^2 \qquad (3.5)$$

or, $\sigma_{it}^2 = \varsigma_t + \gamma_t \sum_{j=1, j\neq i}^{N} W_{j.} \varepsilon_t^2 + \delta_t \sum_{j=1, j\neq i}^{N} W_{j.} \sigma_t^2$.

More compactly,

$$\sigma_t^2 = (I - \delta_t W)^{-1} (\varsigma_t + \gamma_t W \varepsilon_t^2)$$

This resembles the well-known process of Autoregressive Conditional Heteroskedasticity (ARCH) pioneered by Engle (1982) and generalized (GARCH) by Bollerslev (1986) for the study of financial time series. The stability of the variance process requires that the matrix ($I-\delta_t W$) to be invertible. That is $1/\omega_{min} < \delta_t < 1/\omega_{max} = 1$, where ω_{max} and ω_{min} are the respective maximal and minimal elements of the eigenvalues of the row-standardized, contiguity spatial weight matrix W. Furthermore, because the variance must be positive, the sufficient conditions: $\varsigma_t > 0$, $\delta_t \geq 0$, $\gamma_t \geq 0$ are imposed. Therefore, $1 > \delta_t \geq 0$. If $\delta_t = 0$, it is a simple ARCH model. If $\gamma_t = 0$, then the estimated variance σ_t^2 does not vary across the states. The special case of integrated GARCH specification is obtained by assuming $\delta_t + \gamma_t = 1$, which is stable as long as $1 > \delta_t \geq 0$. (see also, Nelson [1990] for the time series discussion of stationarity and persistence of the variance process).

It is our understanding that this is the first attempt to apply a GARCH formulation for spatial analysis in the variance process. Although the estimated variance as a measure of volatility varies over time and may exhibit asymmetry and non-normality, we will not investigate those abnormalities in our spatial model. Our interest is to study the cross-section variation of σ-convergence, both nationally and regionally. We find no evidence to support that regional pattern of σ-convergence mirrors the national process.

4 Model Estimation

Equation (3.4) and (3.5) constitute the complete model with spatial dependence in the mean and in the variance.

The joint normal likelihood of $y_t = [y_{1t}, y_{2t}, \ldots, y_{Nt}]'$ is

$$f(y_t;\theta_t) = \prod_{i=1}^{N} \frac{1}{\sqrt{2\pi\sigma_{it}^2}} \exp\left(-\frac{(y_{it}-\mu_{it})^2}{2\sigma_{it}^2}\right) \left|(I-\rho_t W)\right|$$

where

$$\mu_{it} = \alpha_t + \rho_t \sum_{j=1, j\neq i}^{N} W_{j.} y_t \qquad (3.4)'$$

$$\sigma_{it}^2 = \varsigma_t + \gamma_t \sum_{j=1, j\neq i}^{N} W_{j.}\varepsilon_t^2 + \delta_t \sum_{j=1, j\neq i}^{N} W_{j.}\sigma_t^2 \qquad (3.5)'$$

$$\varsigma_t > 0, \gamma_t \geq 0, \delta_t \geq 0 \quad \text{and} \quad \theta_t = (\alpha_t, \rho_t, \varsigma_t, \gamma_t, \delta_t)'$$

If $\gamma_t = 1 - \delta_t$, the variance follows the integrated GARCH or IGARC(1,1) process. Then, the corresponding log-likelihood function is:

$$\ell\ell(\theta_t \mid y_t) = \sum_{i=1}^{N} \ln f(y_t;\theta_t) = -\frac{N}{2}\ln(2\pi) - \frac{1}{2}\sum_{i=1}^{N}\ln(\sigma_{it}^2) - \frac{1}{2}\sum_{i=1}^{N}\left(\frac{(y_{it}-\mu_{it})^2}{\sigma_{it}^2}\right) + \ln\left|I - \rho_t W\right|$$

The maximum likelihood estimator of θ is obtained by:

$$\hat{\theta}_t = \arg\max \ell\ell(\theta_t \mid y_t)$$

For a small sample used in this study, the normality assumption is likely to be violated. A robust method estimation is quasi-maximum likelihood which has routinely applied in most of financial time series model (see Bolleslev [1986]), and it can be used for spatial model estimation. The asymptotic theory of QMLE for spatially autoregressive model has been developed by Lee [2004]. Finally diagnostic checking of the estimated errors or residuals is performed to make sure that the estimated model is free of spatial correlation. Computations were made using GPE2 econometric package for GAUSS software (Lin [2001]).

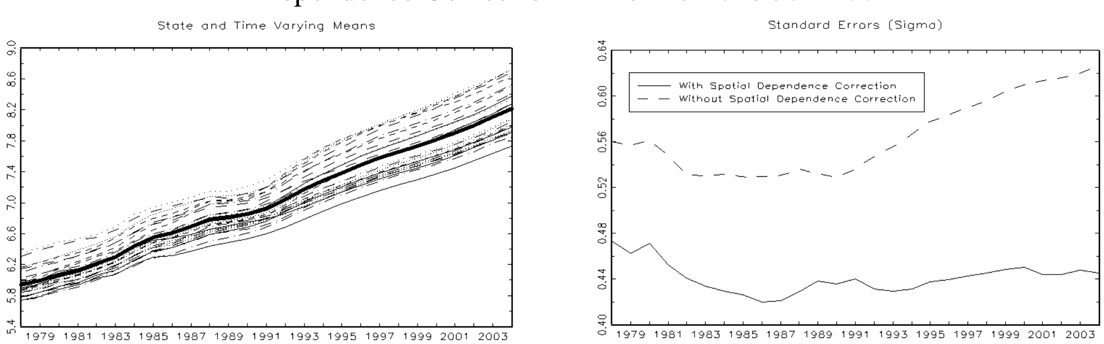
4.1 Empirical Results: Spatial Dependence in the Mean

By considering only the spatial dependence in the mean process (3.4) or (3.4)', the special case of constant variance (across states) σ_t^2 is examined first. It is useful to acknowledge the effects of spatial correlation in the measure of σ-convergence.

Appendix Table A.5 reports the maximum likelihood estimates of (3.4) or (3.4)'. For all years, the parameter of the first-order spatial lag is shown to be statistically significant. Therefore, without considering spatial dependence, the simple calculation of standard deviations is misleading when it is interpreted for σ-convergence. Further, we verify the model performance with two statistics of goodness of fit: log-likelihood and squared correlation of actual and fitted variables.

The maximum likelihood estimate of the standard errors $\hat{\sigma}_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\hat{\varepsilon}_{it}^2}$ is now corrected for the spatial dependence in the mean. In Figure 3, $\hat{\sigma}_t$ is plotted with and without spatial effects (right panel). The difference between the two measures is the extent of spatial effect on the measure of σ-convergence. The divergence of standard errors continues to be the norm, but its trend has been reduced drastically. This confirms that the increasing values of standard deviations are largely due to the increasing spatial dependence after 1990. However, it is probably too optimistic to clam the σ-convergence in the last few years of the sample period. It is also interesting to plot the state-varying means μ_{it} over time to view the development process in detail (left panel). All states are experiencing similar real per capita GDP growth. The solid line in the middle is the average of the estimated mean across states for each year.

Figure 3: Means and Standard Errors of Logged Real Per Capita GDP with Spatial Dependence Correction in the Mean: 1978 - 2004



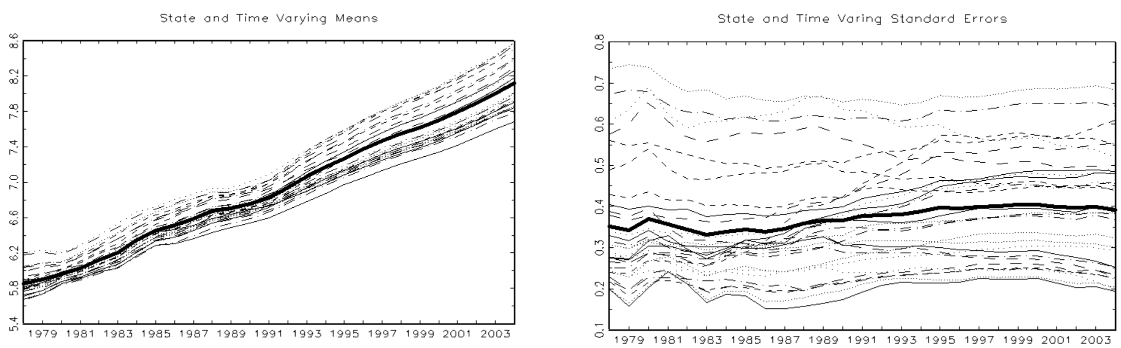
4.2 Empirical Results: Spatial Dependence in the Mean and Variance

Table A.6 reports the parameter estimates for the complete model consisting of equations (3.4) and (3.5) (or equivalently, (3.4)' and (3.5)'). The persistence or coherence in the spatial variance is evident where the sum of estimated unrestricted parameters of δ_t and γ_t equals to 1. Therefore the final model we estimate is a spatial AR(1)-IGARCH(1,1) model. We note that the constant term ζ_t of the variance equation is essentially 0, indicating the equivalent process of exponentially weighted moving average (EWMA) of the variances across states.

By allowing for state-varying means and standard errors in the model specification, the estimated model indicates significant spatial dependence effects in both the mean and variance. In Figure 4, estimated series of μ_{it} (left panel) and σ_{it} (right panel) are plotted. Changes in the estimated mean and standard error over state and time are observed. The solid curve in each of the diagrams represents the average state-varying mean and standard error over time, respectively.

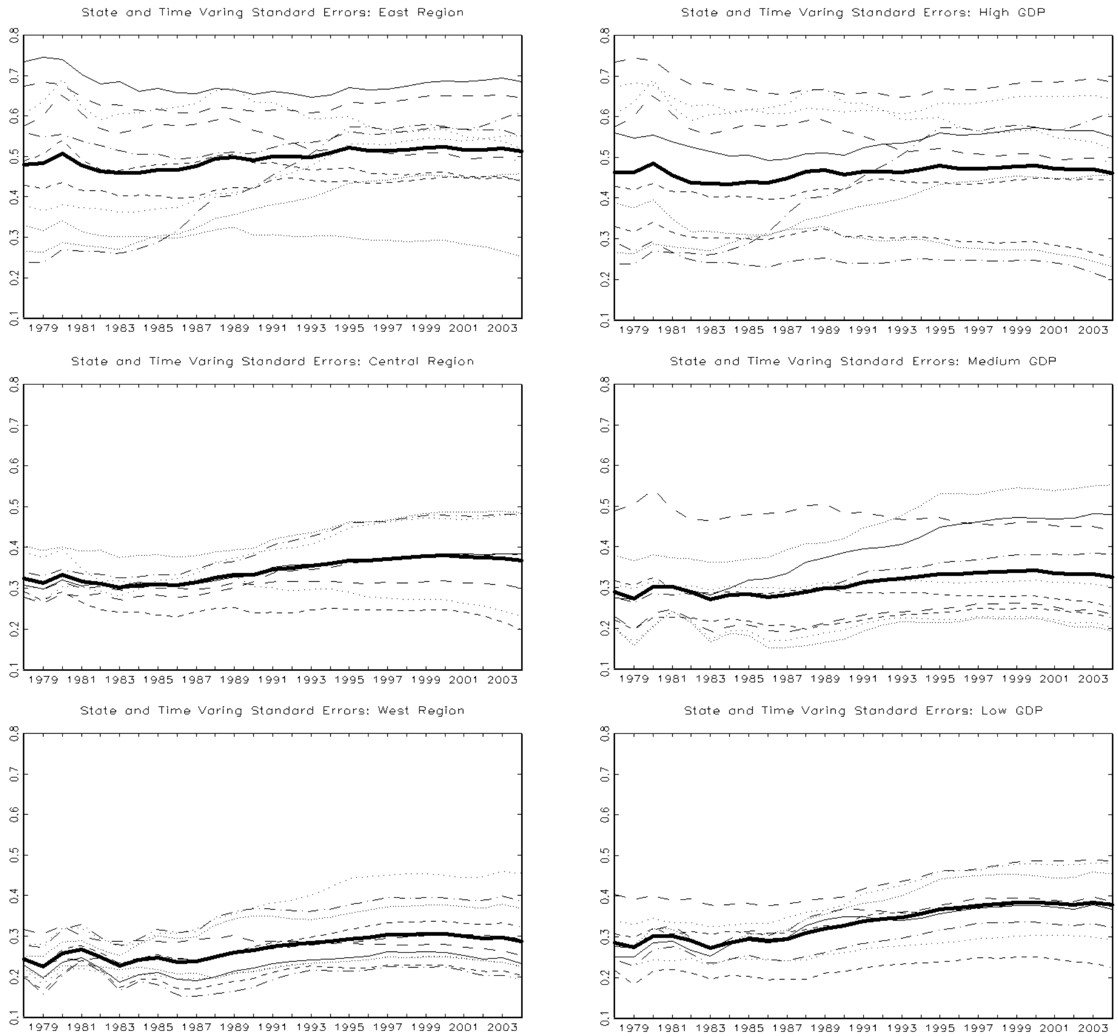
Consistent with previous results, the average of the standard errors corrected for spatial dependence in the mean and variance are almost flat around 0.4. The slight decrease of this average from 1999 is of particularly interesting. This reflects a slow down of the divergent process although it is difficult to infer about the convergence in the 2000s.

Figure 4: Means and Standard Errors of Logged Real Per Capita GDP with Spatial Dependence Correction in the Mean and Variance: 1978 - 2004



One of the advantages of studying state-varying standard errors is to group states with similar characteristics and then study their own pattern of σ-convergence. In addition to grouping states by regional classification (East, Central, and West), we can also group states according to their per capita GDP level. We can then examine σ-convergence or divergence for states in different regions or at different levels of economic development. For the later, we compare states with high per capita GDP (higher than the two-third quantile) with that of the low GDP states (lower than the one-third quantile).

Figure 5: Standard Errors of Logged Real Per Capita GDP with Spatial Dependence Correction in the Mean and Variance for 3 Regions and 3 GDP Levels: 1978 - 2004



Note: See Appendix Table A.1 for the region classification (East, Central, and West) and per capita GDP level classification (High, Medium, and Low).

Looking at state and time-varying patterns of standard errors for the three development regions (East, Central, and West), from the left panels of Figure 5, we find a slight trend reversal from divergence to convergence in the 2000s for all regions. While Central and West regions struggle to catch up, it is not clear that there is a sustainable convergence.

Because of the uneven allocation of natural resources and state preferential policies biased toward coastal provinces and cities in China since 1978, the Eastern region tends to be rich and the Western region poor (see, for example, Lin and Liu [2003]). Based on three levels of per capita GDP (High, Medium, and Low), the right panels of Figure 5 reveal no change or slight divergence in the standard errors for all regions. The conclusions based on either regional or GDP level classification are consistent and essentially the same. The developed provinces and cities have begun to prosper, but the less developed regions are lagging behind.

The Eastern region enjoyed favorable development policies in agriculture, labor migration, and international trade throughout the period studied. Deepening reform in financial and banking industries and a restructuring in government enterprises are expected to speed up the development and convergence process. The current policy is to develop the Central and Western regions by replicating the development strategies used in the Eastern region. The hope is that there will be a reversal of the divergent trend (income inequality) and a tendency of σ-convergence (income equality) in the regional development of China.

5 Conclusion

This paper investigates σ-convergence in China from 1978 to 2004 using a contiguity-based weights matrix for spatial dependence among 30 provinces and cities[4].

To conclude, the methodology of spatial econometrics more accurately measures σ-convergence conditioned on spatial dependence with neighboring states. The finding is that models corrected for spatial dependence have lower standard errors and thus a reduced income disparity across regions. In China, the developed provinces and cities located in the east have begun to prosper, while central and west regions struggle to catch up. However, the analysis does not suggest that there is income equality or convergence at least not until the end of the study period. It is clear that the future direction of regional convergence depends on the on-going policy to develop rural Central and West with substantial regional policy expenditures for income transfer and redistribution.

[4] The alternative formulation is to use economic weights matrix W^* defined in footnote 2. With economic weights matrix W^* in place of contiguity-weights matrix W, we obtain similar empirical results and conclusion about the σ-convergence. Interested readers may request for details of the model estimation results using W^*.

Spatial consideration is equally important for time series correlations in panel data. In this study, we studied cross section correlations of σ-convergence. The time path of conditional variances or standard errors is obtained through conventional comparative static analysis. Extension of dynamic analysis in time and space is the direction of future research.

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Appendix

Table A.1 List of 30 Provinces, Areas, and Cities

	Region Classification	Real Per Capita GDP Level (1978, 2004, and Average of 1978-2004, in 1978 RMB)
Beijing	East	1290.0 11768. 4529.3 (High)
Tianjin	East	1160.0 10679. 3758.1 (High)
Hebei	East	362.00 4053.9 1388.3 (Medium)
Shanxi	Central	365.00 3388.7 1320.2 (Medium)
Inner Mongolia	West	317.00 3195.7 1139.0 (Medium)
Liaoning	East	680.00 5213.1 2087.4 (High)
Jilin	Central	381.00 4215.5 1585.1 (Medium)
Heilongjiang	Central	564.00 3325.2 1414.3 (Medium)
Shanghai	East	2498.0 23601. 8465.3 (High)
Jiangsu	East	430.00 7192.1 2360.7 (High)
Zhejiang	East	331.00 6568.8 2161.3 (High)
Anhui	Central	244.00 2464.7 936.42 (Low)
Fujian	East	273.00 4370.9 1540.7 (Medium)
Jiangxi	Central	276.00 2265.0 903.67 (Low)
Shandong	East	316.00 5767.1 1856.4 (High)
Henan	Central	232.30 2364.8 907.26 (Low)
Hubei	Central	332.00 4301.0 1592.2 (High)
Hunan	Central	286.00 2655.2 1033.5 (Medium)
Guangdong	East	369.00 6157.8 2177.8 (High)
Guangxi	West	225.00 1578.6 647.73 (Low)
Hainan	East	314.00 3874.9 1586.4 (High)
Sichuan	Central	262.00 2205.6 888.54 (Low)
Guizhou	West	175.00 1297.8 551.05 (Low)
Yunnan	West	223.35 2269.1 935.18 (Low)
Xizhang	West	375.00 2513.4 1021.5 (Medium)
Shaanxi	West	291.00 2378.2 949.31 (Low)
Gansu	West	348.00 2299.7 972.51 (Low)
Qinghai	West	428.00 2151.9 935.91 (Low)
Ningxia	West	370.00 3577.4 1412.8 (Medium)
Xinjiang	West	313.00 2516.9 1117.1 (Medium)

Note: GDP level classification of states is based on the average real per capita GDP in constant 1978 value: High (higher than the two-third quantile, or 1585.1), Medium (middle-third quantile), and Low (lower than the one-third quantile, or 972.51).

Table A.2 Estimated Means, Standard Errors and Standardized Moran's Index

	Mean (μ)	Standard Error (σ)	Standardized Moran's Index (P-Value)
1978	5.9346	0.56013	2.6584 (0.0039251)
1979	5.9961	0.55676	2.7718 (0.0027876)
1980	6.0701	0.56146	2.7125 (0.0033386)
1981	6.1242	0.54792	2.8206 (0.0023967)
1982	6.2084	0.53097	2.7544 (0.0029402)
1983	6.2960	0.52988	2.8628 (0.0020993)
1984	6.4355	0.53145	2.9885 (0.0014017)
1985	6.5480	0.52891	3.0035 (0.0013344)
1986	6.6056	0.52952	3.1338 (0.00086267)
1987	6.6893	0.52989	3.1532 (0.00080733)
1988	6.7774	0.53631	3.1213 (0.00090035)
1989	6.8070	0.53208	2.9252 (0.0017212)
1990	6.8503	0.52886	2.9394 (0.0016445)
1991	6.9190	0.53626	3.0055 (0.0013259)
1992	7.0451	0.54719	3.3044 (0.00047582)
1993	7.1710	0.55528	3.4970 (0.00023523)
1994	7.2861	0.56657	3.6392 (0.00013672)
1995	7.3858	0.57789	3.7064 (0.00010513)
1996	7.4846	0.58347	3.7638 (8.3671e-005)
1997	7.5771	0.59009	3.8045 (7.1053e-005)
1998	7.6582	0.59565	3.8270 (6.4850e-005)
1999	7.7340	0.60389	3.8685 (5.4747e-005)
2000	7.8150	0.60973	3.9063 (4.6869e-005)
2001	7.9030	0.61326	4.0051 (3.1002e-005)
2002	7.9988	0.61598	4.0375 (2.7017e-005)
2003	8.1049	0.61963	4.0384 (2.6911e-005)
2004	8.2161	0.62753	4.1492 (1.6679e-005)

Table A.3 Spatial Autocorrelation Function

Order Year	1	2	3	4	5
1978	0.59781* 0.19937	-0.11522 0.37687	0.025526 0.34612	-0.013682 0.086006	0.046249 0.033872
1979	0.62310* 0.19309	-0.092555 0.37650	0.094133 0.34628	-0.020561 0.084783	0.037336 0.033757
1980	0.60763* 0.19673	-0.11643 0.37938	0.056934 0.34535	-0.022621 0.084548	0.042704 0.033457
1981	0.63282* 0.19058	-0.16055 0.38618	-0.020403 0.34941	-0.026004 0.082097	0.040710 0.032400
1982	0.62527* 0.19369	-0.16649 0.38611	-0.077484 0.35024	-0.027129 0.078816	0.041061 0.030942
1983	0.64314* 0.18802	-0.034719 0.37450	-0.036410 0.34851	-0.025381 0.077652	0.038331 0.030608
1984	0.65738* 0.18224	-0.0053865 0.37225	-0.051324 0.35178	-0.032706 0.076353	0.038317 0.030106
1985	0.66053* 0.18136	-0.022479 0.37530	-0.052076 0.35328	-0.035379 0.074879	0.036012 0.029582
1986	0.67817* 0.17509	0.0030911 0.37216	-0.014546 0.35072	-0.035207 0.074337	0.034527 0.029440
1987	0.67326* 0.17521	0.056452 0.36891	0.0099555 0.34798	-0.038310 0.073461	0.034176 0.029128
1988	0.66374* 0.17737	0.060931 0.37003	0.050446 0.34764	-0.038143 0.073453	0.033950 0.029152
1989	0.62478* 0.18776	0.064564 0.37151	0.047506 0.34854	-0.040016 0.072659	0.034494 0.028788
1990	0.62347* 0.18734	0.029978 0.37458	0.038791 0.34802	-0.041641 0.071807	0.036578 0.028336
1991	0.62472* 0.18500	0.038800 0.37653	0.0057588 0.34603	-0.042649 0.071972	0.037282 0.028395
1992	0.67186* 0.17108	0.046519 0.37885	-0.030938 0.34711	-0.048448 0.071812	0.036131 0.028439
1993	0.68706* 0.16398	0.15117 0.37244	-0.045379 0.34782	-0.053160 0.071429	0.032590 0.028507
1994	0.69797* 0.15891	0.21021 0.36747	-0.044004 0.34823	-0.059409 0.071550	0.031180 0.028703
1995	0.69893* 0.15717	0.24481 0.36367	-0.015972 0.34912	-0.065772 0.071852	0.029558 0.028980
1996	0.70206* 0.15537	0.30647 0.35468	0.0032872 0.35065	-0.069394 0.071575	0.027529 0.028999
1997	0.70536* 0.15397	0.34259 0.34895	0.013560 0.35115	-0.073143 0.071425	0.025601 0.029056
1998	0.70829* 0.15303	0.34373 0.34948	0.034576 0.35061	-0.075647 0.071265	0.025295 0.029045
1999	0.71339* 0.15134	0.34995 0.34903	0.038895 0.35057	-0.077114 0.071472	0.025309 0.029160
2000	0.71864* 0.14971	0.36288 0.34643	0.050988 0.35063	-0.077383 0.071436	0.024155 0.029195
2001	0.73508* 0.14491	0.35429 0.34790	0.068604 0.35010	-0.076838 0.071115	0.024386 0.029058
2002	0.73847* 0.14366	0.36567 0.34520	0.060789 0.35079	-0.074636 0.070702	0.024301 0.028867
2003	0.73497* 0.14424	0.38933 0.34085	0.029011 0.35294	-0.070626 0.070391	0.025111 0.028667
2004	0.74884* 0.13956	0.42820 0.33090	0.025418 0.35149	-0.069429 0.070367	0.023532 0.028713

Note: For each order of spatial autocorrelation, the estimated parameters are reported with their corresponding standard errors listed in below. Only the parameters of the first lag are statistically significant.

Table A.4 Spatial Partial Autocorrelation Function

Order / Year	1	2	3	4	5
1978	0.59781* 0.19937	-0.20361 0.28610	0.047316 0.26454	-0.024851 0.075238	0.035967 0.030968
1979	0.62310* 0.19309	-0.21060 0.27984	0.091701 0.25601	-0.026122 0.072118	0.028800 0.029759
1980	0.60763* 0.19673	-0.20272 0.28467	0.085174 0.25984	-0.033334 0.072888	0.034894 0.029951
1981	0.63282* 0.19058	-0.24132 0.28197	0.045433 0.25845	-0.038965 0.069446	0.030865 0.028530
1982	0.62527* 0.19369	-0.23329 0.28378	-0.0054501 0.26345	-0.045762 0.067529	0.030388 0.027673
1983	0.64314* 0.18802	-0.17384 0.27277	0.0061327 0.25290	-0.039279 0.065634	0.029224 0.026931
1984	0.65738* 0.18224	-0.16225 0.26742	-0.0022774 0.25062	-0.049439 0.063335	0.030538 0.025870
1985	0.66053* 0.18136	-0.17068 0.26765	0.0051042 0.25044	-0.051514 0.061751	0.029163 0.025229
1986	0.67817* 0.17509	-0.16213 0.26054	0.029336 0.24127	-0.047948 0.060030	0.028430 0.024579
1987	0.67326* 0.17521	-0.12827 0.26059	0.043406 0.23811	-0.048993 0.059459	0.029393 0.024379
1988	0.66374* 0.17737	-0.11846 0.26361	0.074371 0.23911	-0.046157 0.059741	0.030205 0.024573
1989	0.62478* 0.18776	-0.089866 0.27418	0.072829 0.24929	-0.048917 0.061321	0.032439 0.025024
1990	0.62347* 0.18734	-0.11181 0.27616	0.079271 0.25037	-0.052534 0.060583	0.033945 0.024657
1991	0.62472* 0.18500	-0.10417 0.27612	0.060929 0.24868	-0.055574 0.060462	0.034240 0.024729
1992	0.67186* 0.17108	-0.14046 0.26581	0.055864 0.23674	-0.060917 0.057176	0.033067 0.023419
1993	0.68706* 0.16398	-0.10178 0.26040	0.042754 0.22927	-0.063292 0.055460	0.031747 0.022821
1994	0.69797* 0.15891	-0.082320 0.25648	0.044027 0.22388	-0.067929 0.054344	0.032413 0.022372
1995	0.69893* 0.15717	-0.069695 0.25597	0.059523 0.22142	-0.072847 0.053954	0.033268 0.022199
1996	0.70206* 0.15537	-0.044160 0.25419	0.062472 0.21877	-0.074869 0.053211	0.033205 0.021922
1997	0.70536* 0.15397	-0.031574 0.25318	0.063959 0.21678	-0.077412 0.052679	0.032567 0.021734
1998	0.70829* 0.15303	-0.036478 0.25314	0.076683 0.21528	-0.079767 0.052149	0.032877 0.021506
1999	0.71339* 0.15134	-0.040500 0.25222	0.080669 0.21374	-0.081067 0.051819	0.033305 0.021353
2000	0.71864* 0.14971	-0.039968 0.25054	0.084820 0.21174	-0.080713 0.051358	0.032488 0.021219
2001	0.73508* 0.14491	-0.066958 0.24681	0.10219 0.20701	-0.080617 0.049743	0.032523 0.020512
2002	0.73847* 0.14366	-0.060727 0.24451	0.094301 0.20612	-0.078790 0.049249	0.032316 0.020339
2003	0.73497* 0.14424	-0.039318 0.24400	0.069945 0.20843	-0.075864 0.049455	0.032377 0.020506
2004	0.74884* 0.13956	-0.033043 0.23809	0.063073 0.20207	-0.073479 0.048414	0.030573 0.020229

Note: For each order of spatial autocorrelation, the estimated parameters are reported with their corresponding standard errors listed underneath. Only the parameters of the first lag are statistically significant.

Table A.5 Parameter Estimates: Spatial Dependence in the Mean

$$y_t = \alpha_t + \rho_t W y_t + \varepsilon_t, \quad \varepsilon_t \sim \text{i.i.d. normal}(0, \sigma_t^2 I)$$

	α	ρ	Log-Likelihood	R^2	Estimated Standard Error
1978	2.4376 0.87014	0.59781 0.14455	-21.647	0.26255	0.47292
1979	2.3092 0.81658	0.62310 0.13431	-21.136	0.28637	0.46242
1980	2.4310 0.79636	0.60755 0.13027	-21.580	0.27228	0.47091
1981	2.2996 0.73284	0.63283 0.11816	-20.514	0.29616	0.45195
1982	2.3777 0.71527	0.62527 0.11417	-19.721	0.28666	0.44092
1983	2.3017 0.70764	0.64314 0.11144	-19.369	0.30608	0.43398
1984	2.2609 0.67991	0.65734 0.10526	-19.154	0.32464	0.42941
1985	2.2763 0.61675	0.66053 0.094391	-18.960	0.32796	0.42630
1986	2.1794 0.56022	0.67816 0.085604	-18.632	0.34993	0.41976
1987	2.2384 0.53826	0.67326 0.082172	-18.667	0.34762	0.42080
1988	2.3305 0.51872	0.66374 0.079446	-19.166	0.33838	0.42890
1989	2.6032 0.56283	0.62500 0.085726	-19.545	0.29782	0.43836
1990	2.6279 0.57341	0.62347 0.085978	-19.356	0.29772	0.43575
1991	2.6444 0.56257	0.62473 0.084505	-19.668	0.30296	0.44019
1992	2.3648 0.50597	0.67186 0.075391	-19.402	0.35706	0.43138
1993	2.2968 0.49327	0.68706 0.072006	-19.367	0.38210	0.42915
1994	2.2527 0.50731	0.69797 0.072871	-19.602	0.40071	0.43123
1995	2.2737 0.55431	0.69893 0.078613	-20.065	0.40622	0.43782
1996	2.2778 0.57304	0.70209 0.080085	-20.213	0.41282	0.43959
1997	2.2804 0.58064	0.70536 0.080131	-20.437	0.41836	0.44247
1998	2.2810 0.59639	0.70828 0.081410	-20.640	0.42236	0.44510
1999	2.2646 0.60220	0.71339 0.081496	-20.910	0.42951	0.44846
2000	2.2463 0.60667	0.71867 0.081304	-21.059	0.43657	0.44998
2001	2.1410 0.59398	0.73507 0.078559	-20.815	0.45755	0.44408
2002	2.1386 0.60587	0.73845 0.079122	-20.835	0.46280	0.44389
2003	2.1926 0.63165	0.73498 0.081386	-21.060	0.45987	0.44774
2004	2.1058 0.62774	0.74884 0.079588	-21.007	0.47994	0.44494

Note: The estimated parameter of α and ρ are reported with their corresponding standard errors listed underneath.

Table A.6 Parameter Estimates: Spatial Dependence in the Mean and Variance

$$y_t = \alpha_t + \rho_t W y_t + \varepsilon_t, \quad \varepsilon_t / \sigma_t \sim \text{i.i.d. normal}(0, I)$$

$$\sigma_t^2 = \varsigma_t + (1 - \delta_t) W \varepsilon_t^2 + \delta_t W \sigma_t^2$$

	α	ρ	ς	δ	Log-Likelihood	R^2
1978	2.7793 0.91165	0.52479 0.15991	6.3179e-014 3.4536e-015	0.61938 0.054037	-13.936	0.23916
1979	3.0164 1.0956	0.48760 0.18972	6.8546e-016 4.3871e-016	0.57879 0.066121	-12.261	0.23919
1980	3.8776 1.3135	0.34853 0.22391	8.4965e-014 1.7992e-015	0.60633 0.070619	-14.693	0.17691
1981	3.5923 1.1641	0.40340 0.19666	4.5598e-013 7.1542e-015	0.62990 0.060266	-14.224	0.21010
1982	3.2891 0.93354	0.46253 0.15564	1.8841e-014 2.8301e-015	0.64753 0.049157	-12.843	0.22882
1983	2.8995 0.92534	0.53273 0.15305	3.4796e-015 5.7863e-016	0.60858 0.056140	-11.271	0.26708
1984	3.1459 1.0310	0.50412 0.16626	4.8041e-015 7.6162e-016	0.62391 0.055245	-12.162	0.26783
1985	3.5697 1.0625	0.44672 0.16736	2.2222e-015 7.3795e-016	0.60668 0.059851	-12.216	0.24515
1986	3.2929 1.0276	0.49354 0.16028	1.7048e-014 4.2368e-016	0.58770 0.064821	-11.630	0.27798
1987	3.3508 1.0502	0.48963 0.16246	1.7965e-015 4.6418e-016	0.58820 0.064431	-12.070	0.27657
1988	3.5555 0.99852	0.46534 0.15268	4.8252e-020 5.7043e-016	0.56920 0.063485	-12.773	0.26181
1989	3.8364 0.98238	0.42652 0.14907	7.9370e-017 6.6643e-016	0.58674 0.060847	-13.576	0.22526
1990	3.8111 0.95501	0.43520 0.14468	5.7020e-018 7.4906e-016	0.60595 0.058602	-13.755	0.22950
1991	3.8259 0.92523	0.43836 0.13914	8.2771e-017 9.0571e-016	0.62734 0.052040	-14.559	0.23527
1992	3.6429 0.93974	0.47384 0.13914	1.1920e-014 9.7026e-016	0.62892 0.055937	-14.905	0.27967
1993	3.4602 0.95133	0.50791 0.13897	1.5989e-014 8.2375e-016	0.64601 0.060864	-15.348	0.31178
1994	3.4242 0.97918	0.51969 0.14128	1.2832e-013 6.6375e-016	0.63858 0.065619	-15.724	0.32992
1995	3.4769 0.97315	0.51834 0.13850	5.2022e-017 6.5888e-016	0.62410 0.066132	-16.029	0.33433
1996	3.2928 0.91571	0.55013 0.12850	1.1071e-016 6.1858e-016	0.62373 0.062257	-16.164	0.35371
1997	3.3113 0.95012	0.55345 0.13166	6.0857e-017 6.4485e-016	0.62902 0.061922	-16.544	0.35910
1998	3.2525 0.95137	0.56583 0.13058	6.2323e-015 6.3620e-016	0.62584 0.062950	-16.622	0.36711
1999	3.2271 0.95371	0.57322 0.12969	2.9402e-014 6.1388e-016	0.62130 0.063761	-16.857	0.37500
2000	3.2002 0.93732	0.58121 0.12583	2.9013e-015 6.4301e-016	0.61939 0.061824	-16.972	0.38297
2001	3.0425 0.95631	0.60624 0.12715	1.6489e-016 5.7401e-016	0.61070 0.066009	-16.583	0.40689
2002	2.9634 0.92763	0.62098 0.12181	8.9198e-015 4.9797e-016	0.59559 0.067501	-16.341	0.41699
2003	2.9311 0.90559	0.63040 0.11712	3.2132e-019 5.0237e-016	0.57893 0.067391	-16.326	0.41980
2004	2.5684 0.78989	0.68049 0.10060	1.0680e-014 4.1094e-016	0.56993 0.068942	-15.826	0.45442

Note: The estimated parameter of α and ρ (in the mean) and ς and δ (in the variance) are reported with their corresponding standard errors listed underneath.

Table A.7 Parameter Estimates: Spatial Dependence in the Mean and Variance

$$y_t = \alpha_t + \rho_t W y_t + \varepsilon_t, \quad \varepsilon_t / \sigma_t \sim \text{i.i.d. normal}(0, I)$$

$$\sigma_t^2 = \varsigma_t + \gamma_t W \varepsilon_t^2 + \delta_t W \sigma_t^2$$

	α	ρ	ς	γ	δ	Log-Likelihood	R^2
1978	2.8268 0.69723	0.51556 0.12112	9.2322e-016 1.2471e-015	0.55335 0.15849	0.57002 0.047305	-13.485	0.23602
1979	3.0204 0.86376	0.48632 0.14889	4.8665e-017 5.2278e-016	0.59746 0.15977	0.53113 0.045787	-11.851	0.23870
1980	3.7134 1.0967	0.37575 0.18635	2.0565e-015 1.1811e-015	0.55692 0.14552	0.56527 0.055472	-14.253	0.18838
1981	3.4718 0.96613	0.42284 0.16248	5.0318e-016 1.7521e-015	0.51586 0.14322	0.59377 0.053114	-13.809	0.21833
1982	3.2846 0.76379	0.46241 0.12649	5.2586e-014 1.6118e-015	0.47953 0.13732	0.61359 0.046495	-12.505	0.22877
1983	2.9798 0.74364	0.51881 0.12241	4.2897e-016 8.3657e-016	0.52302 0.14264	0.57177 0.044240	-10.991	0.26176
1984	3.1894 0.84282	0.49636 0.13529	8.6007e-016 1.0568e-015	0.49830 0.13169	0.59056 0.046036	-11.885	0.26464
1985	3.5407 0.88896	0.45066 0.13955	3.7123e-017 1.0665e-015	0.51172 0.13420	0.57588 0.048865	-11.963	0.24688
1986	3.2878 0.86106	0.49380 0.13406	6.2636e-017 6.6382e-016	0.53345 0.14228	0.55454 0.051861	-11.401	0.27810
1987	3.3622 0.89768	0.48741 0.13878	1.8904e-015 7.2083e-016	0.52767 0.14589	0.55515 0.056008	-11.864	0.27560
1988	3.5633 0.87035	0.46376 0.13313	2.6086e-016 8.1214e-016	0.53697 0.15035	0.53902 0.056743	-12.610	0.26112
1989	3.8422 0.84475	0.42513 0.12822	4.8434e-017 9.7751e-016	0.52024 0.14602	0.55661 0.056190	-13.396	0.22468
1990	3.8239 0.82176	0.43271 0.12445	1.6008e-015 1.0759e-015	0.49903 0.13722	0.57625 0.055691	-13.564	0.22847
1991	3.8389 0.80663	0.43589 0.12119	4.9557e-017 1.2634e-015	0.46404 0.12588	0.60104 0.055251	-14.395	0.23424
1992	3.6557 0.82916	0.47148 0.12272	7.7203e-015 1.3378e-015	0.45712 0.12787	0.60343 0.063641	-14.759	0.27860
1993	3.4705 0.82603	0.50598 0.12053	8.4874e-017 1.2918e-015	0.43702 0.12426	0.62131 0.068771	-15.199	0.31091
1994	3.4263 0.85445	0.51903 0.12319	7.8952e-015 1.1950e-015	0.44003 0.12659	0.61479 0.073149	-15.596	0.32962
1995	3.4680 0.86069	0.51931 0.12243	1.6578e-016 1.1438e-015	0.44823 0.12698	0.60188 0.072877	-15.928	0.33478
1996	3.2884 0.80825	0.55045 0.11330	3.7234e-015 1.0862e-015	0.44909 0.12213	0.60113 0.067858	-16.063	0.35386
1997	3.3006 0.83304	0.55462 0.11531	1.7465e-016 1.1602e-015	0.44402 0.11930	0.60675 0.067277	-16.437	0.35963
1998	3.2452 0.83814	0.56656 0.11492	2.6924e-017 1.1071e-015	0.44546 0.11832	0.60366 0.067308	-16.523	0.36744
1999	3.2200 0.84391	0.57394 0.11463	2.8598e-015 1.0842e-015	0.44819 0.11768	0.59954 0.067523	-16.765	0.37531
2000	3.1914 0.83012	0.58217 0.11128	1.8296e-016 1.0943e-015	0.45061 0.11723	0.59738 0.066065	-16.881	0.38340
2001	3.0341 0.84819	0.60714 0.11263	8.1927e-015 9.7319e-016	0.46005 0.11973	0.58796 0.068542	-16.496	0.40729
2002	2.9587 0.82735	0.62138 0.10851	3.2891e-015 8.3513e-016	0.47698 0.12294	0.57172 0.068562	-16.260	0.41716
2003	2.9282 0.81747	0.63058 0.10558	4.5081e-019 7.9296e-016	0.49234 0.12121	0.55543 0.065775	-16.253	0.41988
2004	2.5745 0.72089	0.67958 0.091661	5.4595e-016 6.1651e-016	0.49908 0.11930	0.54677 0.064336	-15.762	0.45405

Note: The estimated parameter of α and ρ (in the mean) and ς, γ, and δ (in the variance) are reported with their corresponding standard errors listed underneath.