Regional Studies, Vol. 33.2, pp. 143–156

US Regional Income Convergence: A Spatial Econometric Perspective

SERGIO J. REY and BRETT D. MONTOURI
Department of Geography, San Diego State University, San Diego, CA 92182, USA

(Received January 1997; in revised form August 1998)

REY S. J. and MONTOURI B. D. (1999) US regional income convergence: a spatial econometric perspective, *Reg. Studies* **33**, 143–156. This study reconsiders the question of US regional economic income convergence from a spatial econometric perspective. Recently developed methods of exploratory spatial data analysis provide new insights on the geographical dynamics of US regional income growth patterns over the 1929–94 period. Strong patterns of both global and local spatial autocorrelation are found throughout the study period, and the magnitude of global spatial autocorrelation is also found to exhibit strong temporal co-movement with regional income dispersion. A spatial econometric analysis of the familiar Baumol specification reveals strong evidence of misspecification due to ignored spatial error dependence. Because of this dependence, shocks originating in one state can spillover into surrounding states, potentially complicating the transitional dynamics of the convergence process.

Regional income convergence   Spatial econometrics   Exploratory spatial data analysis

REY S. J. et MONTOURI B. D. (1999) La convergence du revenu régional aux Etats-Unis: une perspective économétrique, spatiale, *Reg. Studies* **33**, 143–156. Cette étude remet en cause la convergence du revenu économique régional à partir d'une perspective économétrique, spatiale. De nouvelles méthodes qui permettent une première analyse des données spatiales, fournissent un autre aperçu sur la dynamique géographique de la répartition de la croissance du revenu régional aux Etats-Unis de 1929 à 1994. Pendant toute la période étudiée, de fortes autocorrélations géographiques à la fois globales et locales sont à noter. Il s'avère aussi que l'ampleur de l'autocorrélation spatiale, globale va de pair dans le temps avec la dispersion du revenu régional. Une analyse économétrique, spatiale de la spécification bien connue de Baumol fait preuve de la mauvaise spécification due à la dépendance vis à vis des erreurs spatiales à laquelle on n'a pas fait attention. A cause de cette dépendance, des chocs qui proviennent d'un état particulier peuvent avoir des retombées sur les états limitrophes, ce qui risque de compliquer la dynamique transitoire du processus de convergence.

Convergence de revenu régional   Econométrie spatiale
Première analyse des données spatiales

REY S. J. und MONTOURI B. D. (1999) Konvergenz regionaler Einkommen in den Vereinigten Staaten: ein räumlich-ökonometrischer Ausblick, *Reg. Studies* **33**, 143–156. Diese Studie behandelt noch einmal die Frage der Konvergenz regionaler Einkommen in den Vereinigten Staaten vom Standpunkt der räumlichen Ökonometrie aus. Kürzlich entwickelte Methoden einer Analyse räumlicher Untersuchungsdaten verschaffen neue Einsichten in die geographische Dynamik der Muster regionalen Wachstums von Einkommen in den Vereinigten Staaten im Zeitraum 1929–94. Für die genannte Untersuchungsperiode werden robuste Muster globaler wie auch örtlicher räumlicher Autokorrelationen festgestellt, wobei der Umfang letzterer sich zudem als in kräftigem zeitlichem Gleichschritt mit der Streuung regionaler Einkommen erweist. Eine räumliche ökonometrische Analyse der bekannten Baumol Spezifizierung liefert handfeste Beweise fehlerhafter Spezifizierungen infolge unbeachtet gebliebener Abhängigkeit von räumlichen Irrtümern. Dank dieser Abhängigkeit kann der Schock eines Staates in Nachbarstaaten Kreise ziehen, und die Übergangsdynamik des Konvergenzprozesses verkomplizieren.

Konvergenz regionaler Einkommen
Räumliche Ökonometrie
Analyse räumlicher Untersuchungsdaten

INTRODUCTION

A prominent theme in the recent macroeconomic literature has been the topic of economic convergence. As stated by ABRAMOVITZ, 1986, convergence implies a long-run tendency towards the equalization of *per capita* income or product levels. In other words, convergence addresses the important question of whether 'poor' countries, as measured by low per capita incomes, display faster growth rates in per capita income than 'rich' countries with higher per capita incomes? An important contribution by BAUMOL, 1986, has stimulated a large number of studies examining the convergence hypothesis at the international level. Because these studies have been informed by different theoretical perspectives (i.e. neo-classical models versus endogenous growth models) and have employed different empirical strategies (i.e. cross-sectional versus time-series versus panel data), the existing empirical evidence on convergence between nations is subject to much debate (see, for example, BAUMOL, 1986; DE LONG, 1988).

This interest has led to numerous studies of regional income convergence on intra-national scales. Many of these studies focus on the US experience (BARRO and SALA-I-MARTIN, 1991; CARLINO and MILLS, 1993, 1996a, 1996b; CROWN and WHEAT, 1995; BERNARD and JONES, 1996a; VOHRA, 1996; among others), where the consensus is that income convergence has been very strong. In addition to the US studies, regional convergence processes have been examined for: Canadian provinces (COULOMBE and LEE, 1995); Colombian departments (CARDENAS and PONTON, 1995); Mexican states (MALLICK and CARAYANNIS, 1994); British counties (CHATTERJI and DEWHURST, 1996); and other European regions (ARMSTRONG, 1995). By and large, the econometric methods employed to test the convergence hypothesis at the regional scale are virtually identical to those applied in the international studies. In this regard, the key methodological issues examined thus far include: temporal stability (CARLINO and MILLS, 1996b); sectoral composition/contribution (BERNARD and JONES, 1996b, 1996c); reconciliation of the evidence from time-series and cross-sectional studies (BERNARD and DURLAUF, 1996); and interpretation of convergence frameworks (QUAH, 1993a, 1993b).

Despite the fact that theoretical mechanisms of technology diffusion, factor mobility and transfer payments that are argued to drive the regional convergence phenomenon have explicit geographical components, the role of spatial effects in the regional studies has been virtually ignored. Exceptions include ARMSTRONG, 1995, and CHATTERJI and DEWHURST, 1996, where calls are made for a more explicit spatial econometric treatment in regional studies. To date these calls have yet to be answered and, consequently, it is unclear to what extent the current body of empirical evidence on regional income convergence is robust to ignored spatial effects and processes.

This study reconsiders the question of regional economic income convergence from a spatial econometric perspective and aims at two central objectives. The first is to provide new insights into the geographical dynamics of US regional income growth patterns using recently developed methods of exploratory spatial data analysis. The second objective is to suggest and apply a set of spatial econometric methods that extend existing econometric models used in the study of regional income convergence to more fully treat any ignored spatial effects.

In the remainder of the paper we first provide an overview of the recent research on regional income convergence and identify a number of outstanding methodological and substantive issues related to spatial effects. Next, we present an exploratory spatial analysis of US regional income dynamics over the period 1929–94. We then discuss the results of a confirmatory spatial econometric analysis of the regional income convergence hypothesis. The paper closes with a summary and concluding comments.

CONVERGENCE CONCEPTS AND SPATIAL EFFECTS

The recent explosion of interest in regional convergence has not followed a uniform path. Instead, several distinct types of convergence have been suggested in the literature, each being analysed by distinct groups of scholars employing different methods. In this section, we first review the alternative notions of income convergence and methods employed in previous studies. We follow this with a discussion of the role of spatial effects in the econometric analysis of regional income convergence.

Convergence concepts

The first convergence concept pertains to the decline in the cross-sectional dispersion of per capita incomes. Several different measures have been employed to examine this form of convergence including the (unweighted) standard deviation (CARLINO and MILLS, 1996a) and the coefficient of variation (BERNARD and JONES, 1996a) of the log of per capita income. This form of convergence has been referred to as σ-convergence and has attracted much attention in the regional science and economic geography literature (KUZNETS, 1955; EASTERLIN, 1960a, 1960b; WILLIAMSON, 1965; AMOS, 1988, 1989; COUGHLIN and MANDELBAUM, 1988; FAN and CASETTI, 1994).

A second form of convergence, which has primarily been the focus of macroeconomists, occurs when poor regions grow faster than rich regions, resulting in the former eventually catching up to the latter in per capita income levels. To test this form of convergence, numerous studies have employed a cross-sectional specification as follows:

$$\ln\left(\frac{y_{i,t+k}}{y_{i,t}}\right) = \alpha + \beta \ln(y_{i,t}) + \varepsilon_{it} \qquad (1)$$

where: $y_{i,t}$ is per capita income in state i year t; α and β are parameters to be estimated; and ε_{it} is a stochastic error term. Following BAUMOL, 1986, the convention has been to interpret a negative estimate for β as support for the convergence hypothesis since such an estimate would suggest that the growth rates in per capita incomes over the k year period were negatively correlated with starting incomes. Thus, this second form of convergence has been labelled β-convergence.[1]

It is important to recognize that a finding of a negative convergence parameter does not necessarily imply declining cross-sectional variance in income levels (or σ-convergence). QUAH, 1993a, has demonstrated that it is possible for a negative cross-sectional relationship between initial income and growth to coexist with a stable cross-section variance in income levels. This arises from the presence of shocks to country-specific growth rates that can offset the negative β coefficient.[2]

A third perspective on convergence can be found in time-series studies by CARLINO and MILLS, 1996a, 1996b, and BERNARD and DURLAUF, 1995. Here convergence requires that the long run forecasts of income level differences between two economies goes to 0. As noted by BERNARD and DURLAUF, 1996, this definition is violated if shocks to individual economies persist into the indefinite future. In the presence of such shocks, the income series would contain unit roots and, because of this stationarity requirement, this concept of convergence has been referred to as *stochastic convergence.*

The results from the cross-sectional (β and σ-convergence) and time-series studies (stochastic convergence) seem to be at odds. Cross-sectional tests (BARRO and SALA-I-MARTIN, 1991, 1992; MANKIW *et al.*, 1992) generally find evidence of convergence, while the time series tests (QUAH, 1992; BERNARD and DURLAUF, 1995) have tended to fail to reject the no-convergence hypothesis. In an attempt to reconcile these findings, CARLINO and MILLS, 1996a, argue that, in the case of the US over the period 1929–90, there is evidence of unit roots in state income levels and persistent state-specific shocks which implies a lack of stochastic convergence. However, they demonstrate that, by allowing for a trend break in 1946, stationary state-specific shocks are found in the two sub-periods which are consistent with stochastic convergence. They also report strong evidence in support of the cross-sectional notion of β convergence.

Spatial effects in the analysis of regional income convergence

In all three notions of convergence, the unit of analysis has been an individual region observed either as part of a cross section or in a time-series. Implicitly, each region has been viewed as an independent entity and the potential for observational interactions across space has gone largely ignored. While technology spill-overs (e.g. KRUGMAN, 1987; and JONES, 1997) have been identified as key mechanisms that may lead to convergence, the geographical dimensions of these spill-overs have yet to be explored. At the same time, BERNARD and JONES, 1996b, suggest that comparative advantage leading to regional specialization in tradable goods sectors may result in a lack of convergence at the aggregate level. While theoretically intriguing, such arguments have not been formally incorporated in the empirical models used to examine the convergence hypothesis at the regional scale. However, by recognizing such forms of interaction as cases of *substantive spatial dependence* (ANSELIN and REY, 1991), a rich body of spatial process models becomes available to the study of regional income convergence.

In addition to the substantive form of spatial dependence, the geographical organization of the observations in regional convergence studies may give rise to a second type of spatial dependence. This can result from a mismatch between the spatial boundaries of the market processes under study and the administrative boundaries used to organize the data. Spatial dependence due to this form of boundary mismatch has been referred to as *nuisance dependence* (*ibid.*), since it is reflected in a spatially autocorrelated error term.

Both substantive and nuisance forms of spatial dependence can result in major model misspecification if they are ignored (ANSELIN, 1988). Recent developments in spatial econometrics offer procedures for testing for the potential presence of these misspecifications and suggests the proper estimators for models that treat the spatial dependence explicitly (for recent reviews, see ANSELIN and FLORAX, 1995; ANSELIN and BERA, 1997; and ANSELIN and REY, 1997). To date these methods have not been extensively applied in convergence studies. In a later section, we outline the application of these methods to the analysis of regional income convergence in the US.

A second type of spatial effect relevant to convergence studies is spatial heterogeneity which reflects a general instability of a behavioural relationship across the observational units. For example, CARLINO and MILLS, 1996a, argue that the traditional cross-sectional analysis of convergence assumes that all regions have an identical rate of convergence. Because of this, they eschew cross-sectional methods in favour of a time-series investigation.[3] In contrast, CHATTERJI and DEWHURST, 1996, provide an interesting framework that allows for spatial heterogeneity in the form of *convergence clubs*.[4] Therefore, we argue that, even in a pure cross-sectional analysis, an analysis of regional variations in rates of income convergence is not precluded.

Our empirical analysis focuses on the case of the US during the period 1929–94. We consider both σ and β-convergence over this period as well as investigate the spatial dimensions of US income dynamics. Attention is first directed towards σ-convergence and the related spatial patterns, followed by a spatial econometric analysis of β-convergence.[5]

EXPLORATORY SPATIAL DATA ANALYSIS OF US INCOME CONVERGENCE

σ-convergence and global spatial autocorrelation

While σ-convergence has attracted a good deal of attention, it is important to note that this measure is

Fig. 1. US relative income convergence and spatial autocorrelation, 1929–94

only concerned with spread-dispersion (2nd moment) of the state income distribution. We argue that the current focus on the dispersion of the state income distributions may mask nontrivial geographical patterns that may also fluctuate over time. Therefore, in addition to analysing the dynamic behaviour of income dispersion for the 48 conterminous states over time, we will also explore the geographic dimensions of these distributions.

Fig. 1 displays the by now familiar pattern of declining per capita income dispersion in the US, as measured by the coefficient of variation for the natural log of real state per capita incomes. The long term trend appears to have been towards convergence with a few exceptions, most notably the depression years (1929–32) and the slight increase in dispersion over the 1979–89 period. The most rapid period of convergence was in the early 1940s.[6]

Fig. 1 also portrays the path of spatial autocorrelation for the state incomes over the same time period.[7] The measure is based on the Moran's I statistic expressed as:

$$\mathrm{I}_t = \left(\frac{n}{s_o}\right) \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} x_{i,t} x_{j,t}}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{i,t} x_{j,t}} \tag{2}$$

where: $w_{ij,t}$ is an element of a binary spatial weights matrix **W** such that $w_{ij} = 1$ if states i and j share a border and zero otherwise; $x_{i,t}$ is the natural log of real per capita income in state i in year t (measured as a deviation from the mean value for that year); n is the number of states; and s_o is a scaling factor equal to the sum of all the elements of **W**.[8]

An analysis of the natural logarithms of the per capita income values revealed no evidence of departures from normality; thus we based the significance of the Moran's I statistics on the normality assumption.[9] There is very strong evidence of spatial dependence as the statistics are significant at $p = 0{\cdot}01$ for all years. Interestingly, the measure of spatial autocorrelation also tends to co-move with the measure of income dispersion. In fact, the simple correlation between the Moran's I statistic and the coefficient of variation for the incomes is 0·785 over the 66-year period. In particular, the spatial dependence tends to reach its minimum values in 1981–82, followed by rapid increases from 1983–88, coinciding with the period some have previously identified with a reversal of long term regional income convergence (Amos, 1989; Coughlin and Mandelbaum, 1988; Braun, 1991; Rowley *et al.*, 1991).

Several impressions may be taken away from Fig. 1. First, in any given year the state income distribution displays a high degree of spatial autocorrelation. Although the magnitude of the dependence seems to weaken as the income dispersion lessens, the dependence is still significant. This suggests that the evolution of the state income distribution appears to be clustered in nature. That is, the relatively high (low) income states tend to be located nearby other high (low) income states more often than would be expected due to random chance. If this is the case, then each state should not be viewed as an independent observation, as has been implicitly assumed in previous studies of regional income convergence.

The second impression is that the co-movement between income dispersion and spatial dependence may reflect a dynamic characteristic of the regional clustering. There are several intriguing questions that can be asked about this relationship. First, what is the nature of the weakening (strengthening) of the regional clustering in times of income convergence (divergence)? Two possibilities can be identified. On the one hand, an increase in spatial dependence could be due to the states in each cluster becoming more similar in their income levels. On the other hand, an increase in spatial dependence could also be due to newly formed clusters emerging during a period of increased income dispersion. The second question addresses the issue of spatial stationarity: to what extent does the global measure of spatial autocorrelation mask pockets of non-stationarity or so called 'hot-spots' that deviate from the overall pattern? Unfortunately, Moran's I, which is a global measure of spatial dependence, does not allow us to distinguish between these possibilities. For that we turn to a more disaggregated view of the structure of spatial dependence in US regional incomes.

σ-convergence and local spatial autocorrelation

Figs. 2 and 3 provide a more disaggregated view of the nature of the spatial autocorrelation for the initial (Fig. 2) and terminal (Fig. 3) years.[10] Each figure contains a Moran scatterplot, suggested by Anselin, 1993, which plots the standardized income of a state against its spatial lag (also standardized). A state's spatial lag is a weighted average of the incomes of its neighbouring states, with the weights being obtained from the simple contiguity matrix. The four different quadrants of the scatterplot identify four types of local spatial association between a state and its neighbours: (HH) a

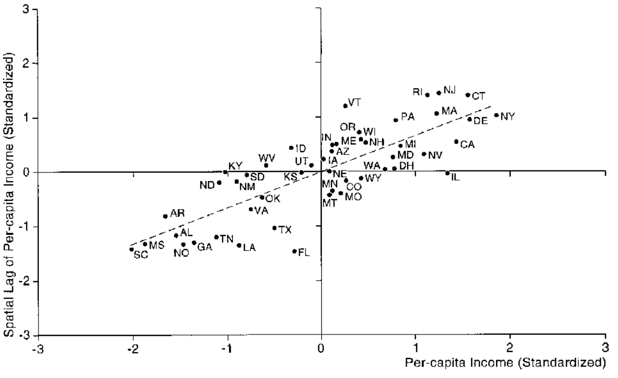

Fig. 2. Moran scatterplot real state per capita income, 1929

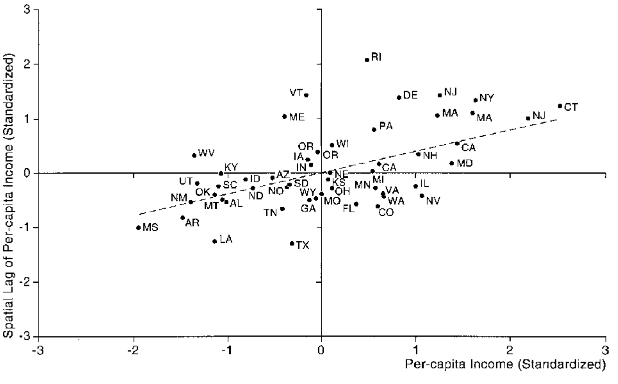

Fig. 3. Moran scatterplot real state per capita income, 1994

high income state with high income neighbours (quadrant I); (LH) a low income state surrounded by high income neighbours (quadrant II); (LL) a low income state surrounded by low income neighbours (quadrant III); and (HL) a high income state with low income neighbours (quadrant IV). Quadrants I and III pertain to positive forms of spatial dependence while the remaining two represent negative spatial dependence. Used in conjunction with the global measures of spatial dependence (underlying Fig. 1), the scatterplot provides a visual impression on the overall stability of the global pattern of dependence, as well as the ability to identify local regimes of spatial dependence that may depart from the overall pattern.

A slightly different perspective from the scatterplot is found in Figs. 4 and 5, where the local Moran statistics (ANSELIN, 1995) are mapped for each state at the initial and terminal years of our sample. The local Moran for state i takes the following form:

$$I_{i,t} = \left(\frac{x_i}{m_o}\right) \sum_{j=1}^{n} w_{ij} x_{j,t} \tag{3}$$

with:

$$m_o = \sum_{i}^{n} x_{i,t}^2$$

Viewing Figs. 2–5 together suggests that there has been a slight modification of the overall structure of spatial dependence between the two years. More specifically, membership in quadrant I of the scatterplot declines (Fig. 3 vs. Fig. 2) and the states demonstrating this change tend to be located on the border of a cluster, while the core members remain (Fig. 5 vs. Fig. 4). For example, Virginia, found in quadrant III and on the northern border of the LL cluster of south-eastern states in 1929, moved into quadrant IV (HL) by the end of the study period. Nevada, in quadrant I in 1929 and on the eastern border of the HH cluster on the west, moves to quadrant IV in 1994, a relatively high income state bordering poorer states.[11]

The results from the application of the local Moran statistics to the income values in each of the years in the sample are summarized in Table 1. Reported in the third column is the number of years, out of the 66, for which the local statistic provides indications of clustering using a pseudo-significance level of $p = 0{\cdot}05$. The significance level is based on a conditional randomization approach involving 1,000 random permutations of the neighbouring states for each observation. Also reported is the number of years the significant local Moran value falls in each of the four quadrants of the Moran's scatterplot.

The results in Table 1 illustrate several points. The first thing to note is that the local pattern of spatial association tends to reflect the global trend of positive spatial association reported earlier. More specifically, over 95% of the local indicators that are significant fall in either quadrants I or III of the scatterplot, reflecting HH and LL clustering respectively. At the same time the remaining significant indicators revealing negative spatial association are roughly divided between HL (i.e. 'diamond in the rough') and LH (i.e. 'doughnut') forms of clustering. This suggests that these deviations from the global trend are not dominated by a particular form of negative spatial association.

The second thing to note is that two strong regional clusters seem to be persistent throughout the 66 years. The first is the Northeast–Mid Atlantic cluster of high income states including Massachusetts, New York, Pennsylvania, Connecticut, Rhode Island and Delaware, each of which appears in quadrant I when its local Moran is significant. The second cluster is in the Southeast consisting of the relatively low income states of North Carolina, Tennessee, Alabama, Mississippi, Georgia, South Carolina, Arkansas and Louisiana, each of which falls in quadrant III the vast majority of years. The results in column three provide fairly strong evidence that the clustering in these two regions is not due to chance alone. It appears, therefore, that the positive correlation between the global Moran's I and the measure of income dispersion, depicted in Fig. 1, is due to a strengthening of the regional clusters during periods of income divergence, rather than the appearance of newly formed clusters.

While the exploratory analysis of income levels has

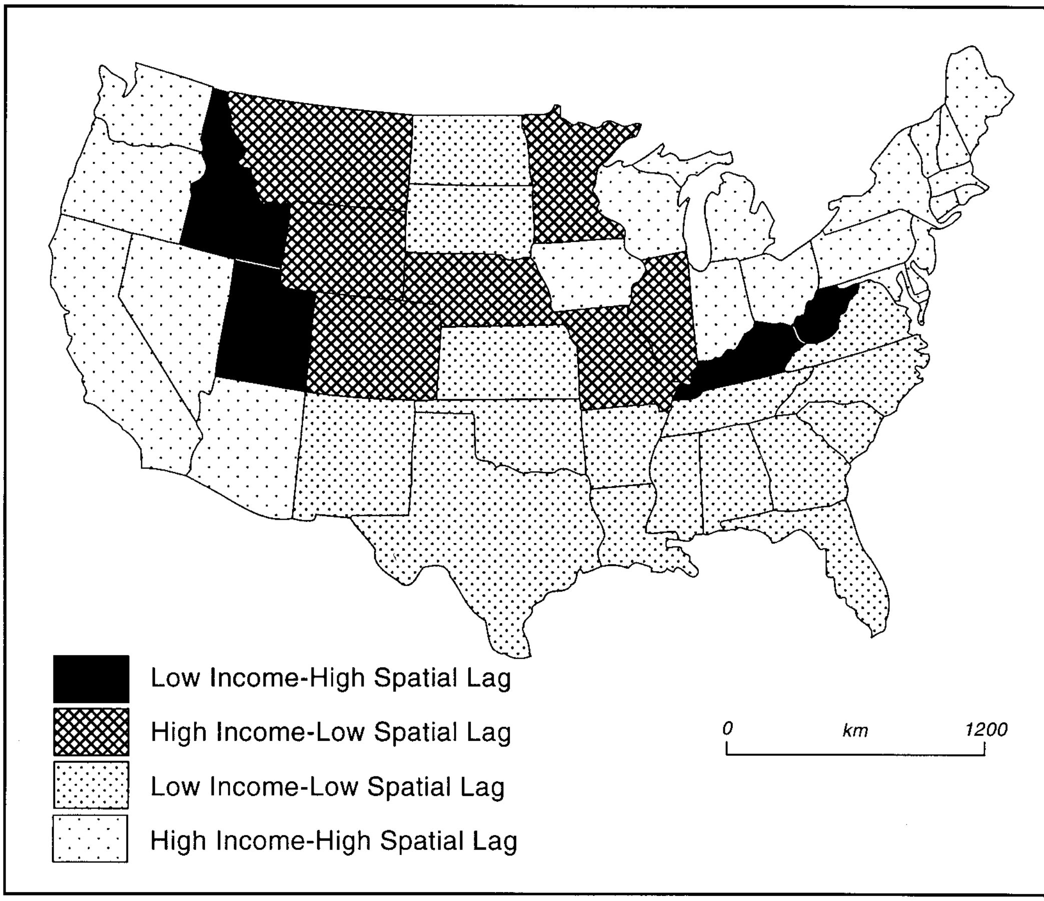

Fig. 4. Local Moran statistics per capita income, 1929

revealed very strong evidence of spatial autocorrelation over the sample period, the convergence hypothesis is concerned with the relationship between the growth rate in the incomes and their starting levels. A spatial analysis of the growth rates between 1929–94 indicates that these rates are also highly spatially autocorrelated as the z-value associated with Moran's I using the simple contiguity matrix is 7·01 which is significant at $p = 0{\cdot}001$. Fig. 6 contains the Moran scatterplot for the growth rates over the period. The overall pattern of the local measures of spatial association is positive as reflected by the slope of the trend line which is driven by the majority of the states falling in quadrants I and III.

Interestingly, a comparison of the pattern of spatial association of the growth rates in Fig. 6 with the pattern of spatial association in the initial incomes in Fig. 2 suggests an inverse relationship. More specifically, it appears that the states that had high initial incomes and were surrounded by high income states, also had growth rates that were below average as did their neighbours. A similar finding holds for states displaying negative spatial associations in their initial incomes that were in quadrant II (IV) in Fig. 2, and display negative spatial associations in their growth rates that are in quadrant IV (II) in Fig. 6.

These patterns raise an important question: what is the extent to which the similarity of the spatial patterns in the growth rates and the starting income levels may be due solely to the convergence process? If the unconditional convergence model was correct, then the *a priori* expectation would be for the spatial pattern in the growth rates to be the inverse of the pattern for the initial incomes. On the other hand it remains to be seen if any spatial structure remains in the unexplained variation of the growth rates after conditioning on the starting levels. We now turn to a confirmatory spatial econometric analysis of the convergence hypothesis in order to provide insights to this question.

CONFIRMATORY SPATIAL ANALYSIS OF β-CONVERGENCE

Our point of departure for the confirmatory analysis of regional income convergence is the unconditional model of equation (1) which is rewritten here in vector notation:

$$\ln\left(\frac{y_{t+k}}{y_t}\right) = \alpha + \beta \ln(y_t) + \varepsilon_t \tag{4}$$

where the vector y_t now contains the observations on real per capita income from all states in a given year.

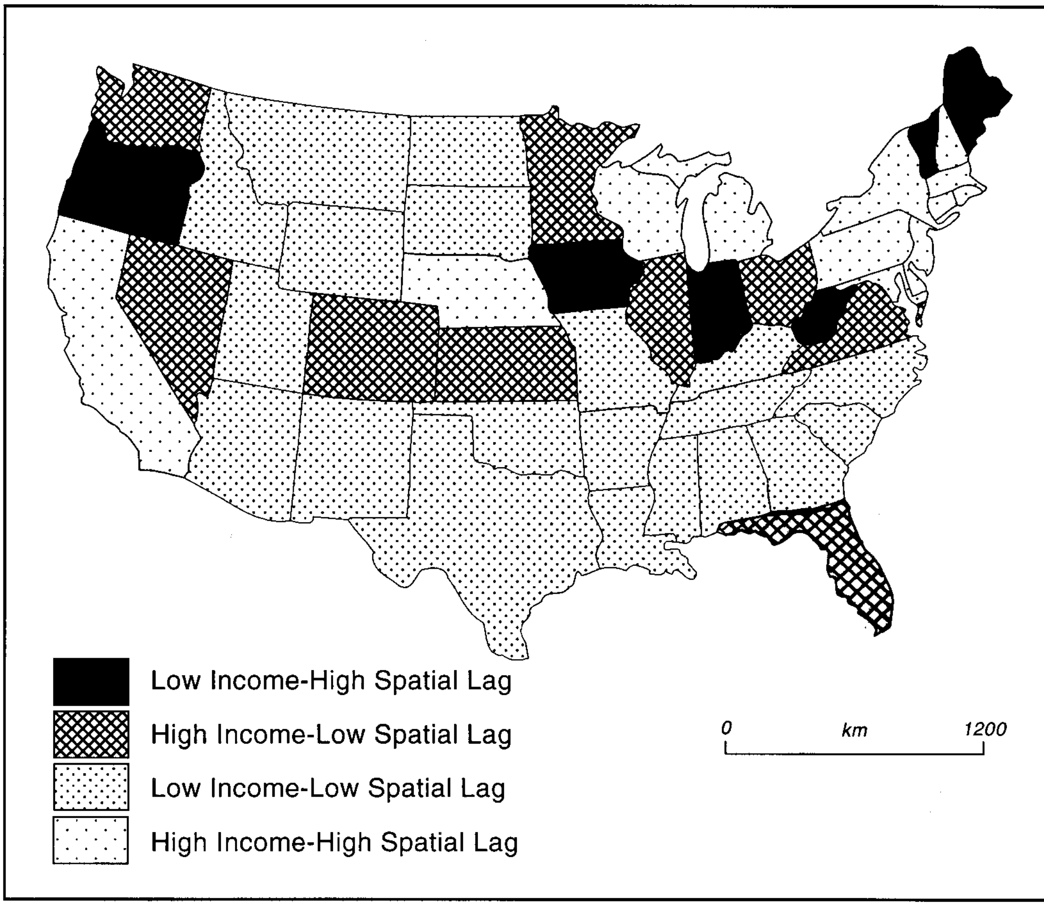

Fig. 5. Local Moran statistics per capita income, 1994

We extend this specification to deal with the presence of spatial dependence in the US income data.[12]

Spatial dependence models

In most applications of the Baumol framework to the US, an implicit assumption is that the error terms from different states are independent:

$$E\left[\varepsilon_t \varepsilon_t'\right] = \sigma_t^2 I \tag{5}$$

However, in such a cross-sectional context in which the observational units are spatially organized, this assumption may be overly restrictive. In particular, the possibility exists for spatial spill-overs across state boundaries leading to forms of spatial dependence that would violate these assumptions. Below we outline alternative specifications that are appropriate for these different forms of spatial dependence.

Spatial error model. This specification is relevant when the dependence works through the error process in that the errors from different states may display spatial covariance. Using vector notation, the error term would be expressed as:

$$\begin{aligned} \varepsilon_t &= \zeta W \varepsilon_t + u_t \\ \varepsilon_t &= (I - \zeta W)^{-1} u_t \end{aligned} \tag{6}$$

where: ζ is a scalar spatial error coefficient; and $u \sim N(0, \sigma^2 I)$. In this case the original error term has the following non-spherical covariance matrix:

$$E[\varepsilon_t \varepsilon_t'] = (I - \zeta W)^{-1} \sigma^2 I (I - \zeta W)^{-1'} \tag{7}$$

As is well known, use of ordinary least squares (OLS) in the presence of non-spherical errors would yield unbiased estimates for the convergence (and intercept) parameter, but a biased estimate of the parameter's variance. Thus, inferences based on the OLS estimates may be misleading. Instead, inferences about the convergence process should be based on the spatial error model estimated via maximum likelihood or general methods of moments.

From a spatial process perspective, the spatial error specification has an interesting interpretation when applied to the convergence hypothesis. This can be seen by substituting equation (6) into equation (4):

$$\ln\left(\frac{y_{t+k}}{y_t}\right) = \alpha + \beta \ln(y_t) + (I - \zeta W)^{-1} u_t \tag{8}$$

Table 1. Summary of local measures of spatial association: real per capita income, 1929–94

	State	$p < 0{\cdot}05$	Q1	Q2	Q3	Q4
AL	Alabama	55	0	0	55	0
AZ	Arizona	0	0	0	0	0
AR	Arkansas	62	0	0	62	0
CA	California	5	5	0	0	0
CO	Colorado	1	0	0	0	1
CT	Connecticut	55	55	0	0	0
DE	Delaware	59	59	0	0	0
FL	Florida	25	0	0	19	6
GA	Georgia	56	0	0	56	0
ID	Idaho	15	9	6	0	0
IL	Illinois	0	0	0	0	0
IN	Indiana	0	0	0	0	0
IA	Iowa	1	1	0	0	0
KS	Kansas	0	0	0	0	0
KY	Kentucky	0	0	0	0	0
LA	Louisiana	66	0	0	66	0
ME	Maine	0	0	0	0	0
MD	Maryland	0	0	0	0	0
MA	Massachusetts	46	46	0	0	0
MI	Michigan	0	0	0	0	0
MN	Minnesota	2	0	0	0	2
MS	Mississippi	66	0	0	66	0
MO	Missouri	11	0	0	2	9
MT	Montana	6	0	0	6	0
NE	Nebraska	0	0	0	0	0
NV	Nevada	2	2	0	0	0
NH	New Hampshire	0	0	0	0	0
NJ	New Jersey	55	55	0	0	0
NM	New Mexico	0	0	0	0	0
NY	New York	61	61	0	0	0
NC	North Carolina	52	0	0	52	0
ND	North Dakota	0	0	0	0	0
OH	Ohio	0	0	0	0	0
OK	Oklahoma	0	0	0	0	0
OR	Oregon	46	46	0	0	0
PA	Pennsylvania	64	64	0	0	0
RI	Rhode Island	64	62	2	0	0
SC	South Carolina	15	0	0	15	0
SD	South Dakota	1	1	0	0	0
TN	Tennessee	66	0	0	66	0
TX	Texas	61	0	0	54	7
UT	Utah	0	0	0	0	0
VT	Vermont	34	15	19	0	0
VA	Virginia	21	0	0	21	0
WA	Washington	0	0	0	0	0
WV	West Virginia	0	0	0	0	0
WI	Wisconsin	6	6	0	0	0
WY	Wyoming	4	0	0	3	1

Notes: $p < 0{\cdot}05$, number of years local statistic is significant at 0·05. Q1, number of years local statistic is in quadrant 1 of Moran's scatterplot; Q2, number of years local statistic is in quadrant 2 of Moran's scatterplot; Q3, number of years local statistic is in quadrant 3 of Moran's scatterplot; Q4, number of years local statistic is in quadrant 4 of Moran's scatterplot.

From equation (8) it is evident that a random shock introduced into a specific state will not only affect the growth rate in that state but, through the spatial transformation $(I - \zeta W)^{-1}$, will impact the growth rates of other states. Moreover, while any state has a limited number of neighbours, as is expressed by the sparseness of the spatial weights matrix, the inverse operator in the transformation defines an error covariance structure that diffuses state-specific shocks not only to that state's neighbours but throughout the system.

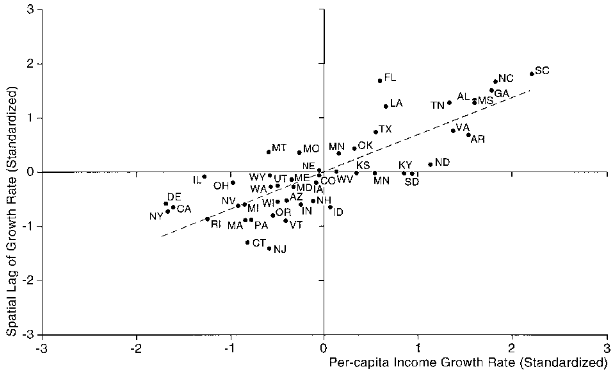

Fig. 6. Moran scatterplot state income growth rates, 1929–94

Spatial lag model. Spatial dependence can also take on several substantive forms which may be relevant to the convergence hypothesis. The first form of substantive dependence we consider is incorporated into the unconditional specification through a spatial lag:

$$\ln\left(\frac{y_{t+k}}{y_t}\right) = \alpha + \beta \ln(y_t) + \rho W \ln\left(\frac{y_{t+k}}{y_t}\right) + \varepsilon_t \qquad (9)$$

where: ρ is the scalar spatial autoregressive parameter and all other terms are as previously defined. This specification can be interpreted in a number of ways (ANSELIN and BERA, 1997). From a filtering perspective (GETIS, 1990, 1995), the focus is on the nature of the convergence relationship after the spatial effect has been controlled for:

$$(I - \rho W)\ln\left(\frac{y_{t+k}}{y_t}\right) = \alpha + \beta \ln(y_t) + \varepsilon_t \qquad (10)$$

Alternatively, when the interest centres on the spatial dependence in the dependent variable, the question arises as to how the growth rate in a state may relate to those in its surrounding states after conditioning on the starting year levels of income. This perspective is important because it addresses the question of whether the indications of spatial dependence in the growth rates, reported in the univariate tests of spatial dependence in the previous section, may be an artifact of the convergence process operating on initial incomes that were spatially autocorrelated.

Finally, from the perspective of the data generating process for the lag specification, the expected value of the income growth rates can be expressed as follows:

$$E\left[\ln\left(\frac{y_{t+k}}{y_t}\right)\right] = E[(I-\rho W)^{-1}(\alpha+\beta\ln(y_t))] + E[(I-\rho W)^{-1}\varepsilon_t] \tag{11}$$

This reveals how the expected value of the growth rate of each state's income is related not only to its own starting level of income, but to those in other states as well. While the expected value of the error term is 0, a non-zero realization of a shock to a particular state will impact not only on that state but, through the spatial transformation, will also affect other states (in the same fashion as for the error model).

OLS applied to the lag specification is inconsistent due to the simultaneity introduced through the spatial lag. Instead a number of alternative estimators based on maximum likelihood and instrumental variables have been suggested (ANSELIN, 1988).

Spatial cross-regressive model. A second possibility for dealing with substantive spatial spill-over effects is the cross-regressive model in which the spatial lag of starting per capita incomes is added to the original specification:

$$\ln\left(\frac{y_{t+k}}{y_t}\right) = \alpha+\beta\ln(y_t)+\tau W\ln(y_t)+\varepsilon_t \tag{12}$$

In contrast to the lag model, where the spatial dependence in the variation unaccounted for by the unconditional model is reflected in the growth rates in per capita income over the period under consideration, in the cross-regressive model the remaining spatial dependence is with respect to the starting levels of income. Because the latter variable and its spatial lag are exogenous, estimation of the cross-regressive model can be based on OLS. We consider this specification in the analysis that follows because the erroneous omission of the cross-lag term would lead to spatially autocorrelated errors. Since each of these three spatial income convergence models hold different interpretations for the nature of the convergence process, it becomes important to discriminate between these three as well as the original aspatial convergence model of equation (4).

Empirical results: unconditional convergence models

In Table 2, we present the results of the estimation of a cross-sectional regression of the unconditional convergence model for the 48 conterminous states. To allow for the trend break identified by CARLINO and MILLS, 1996a, we estimate models for three different sample periods: 1929–94, 1929–45 and 1946–94. The results provide much support for β-convergence as the overall fit of the simple specification is generally high, with an adjusted R^2 above 0·70 in all three samples. Additionally, the regressions from each sample yield highly significant and negative coefficients for the starting income levels, confirming the consensus result of β-convergence for the US states.

In column 5 of Table 2, the implied annual rate of convergence over the entire study period is reported to be 1·9% which is in general agreement with previous findings of BARRO and SALA-I-MARTIN, 1991. However, it appears that the rate of convergence was not stable over the entire period, as the implied rate in the earlier years (1929–45) is roughly twice that of the later years (1946–94). This instability of the convergence rate also concurs with the findings of CARLINO and MILLS, 1996a, who report more rapid cross-sectional convergence in the earlier period. We return to this issue below.

The bottom portion of Table 2 reports a number of diagnostics for the presence of spatial effects. Three different tests for spatial dependence are included: a Moran's I test; and two robust Lagrange multiplier tests. As reported in ANSELIN and REY, 1991, the first test is very powerful against both forms of spatial

Table 2. Unconditional model OLS estimation

	R^2 (σ^2)	AIC[1]	β (p-value)[2]	Convergence rate (θ)[3]
1929–94	0·913 (0·007)	−101·956	−0·708 (0·000)	0·019
1929–45	0·823 (0·005)	−111·662	−0·427 (0·000)	0·035
1946–94	0·703 (0·007)	−97·570	−0·555 (0·000)	0·017

	Robust LM (error)[4] p-value	Robust LM (lag)[5] p-value	Moran's I (error)[6] MI/p-value
Diagnostics for spatial dependence			
1929–94	0·318	0·273	0·162/0·037
1929–45	0·020	0·144	0·388/0·000
1946–94	0·109	0·165	0·354/0·000

	Breusch-Pagan test p-value
Diagnostics for heteroscedasticity	
1929–94	0·857
1929–45	0·155
1946–94	0·142

Notes: 1. Value of the Akaike Information Criterion.
2. Estimate for β and its p-value.
3. The convergence rate θ is obtained using $\theta=\ln(\beta+1)/-k$, where k is the number of years in the period.
4. P-value for the robust Lagrange Multiplier test for error dependence.
5. P-value for the robust Lagrange Multiplier test for lag dependence.
6. Value of Moran's I for the error term, along with its probability.

dependence, the spatial lag and spatial error autocorrelation; unfortunately, it does not allow for the discrimination between these two forms of misspecification. In contrast, the robust tests have displayed good power against a specific alternative in an extensive set of Monte Carlo experiments (ANSELIN *et al.*, 1996). These properties are reflected here, as Moran's I provides very strong evidence of spatial dependence in each sample. However, following the strategy suggested by ANSELIN and REY, 1991, the robust tests point to the presence of spatial error autocorrelation rather than the spatial lag. While there is very strong evidence of spatial dependence, a spatially adjusted Breusch–Pagan test for heteroscedasticity is not significant in any of the sub-samples. Thus, in the remainder of the empirical analysis we limit attention to the spatial dependence models and omit further consideration of the spatial heterogeneity models.

Table 3 reports the estimation results for the different spatial dependence models over the three periods. Based on the value of the Akaike Information Criterion (AIC), the fit of each of the three spatial models is superior to that of the original unconditional model from Table 2.[13] As expected from the findings of the diagnostic tests in Table 2, the spatial error model achieves the best fit for each of the periods. This suggests that the original unconditional model, which has been the work-horse of much previous research, suffers from a misspecification due to omitted spatial dependence. It also implies that the finding of significant spatial autocorrelation in the growth rates reported above is not explained entirely by the convergence hypothesis coupled with the spatial dependence of the starting income levels.

The fourth column of the table reports the asymptotic p-values for the coefficient on the spatial variable for each model and period. The coefficients on the error and lag terms are significant in both of the sub-periods, while only marginally so for the lag and not for the error term when the entire period is considered. In contrast, the coefficient on the spatial lag of the initial income levels in the cross regressive model is never significant. In fact, the diagnostics indicate that there is significant spatial dependence remaining in the cross-regressive model.

The bottom of Table 3 reports the implied convergence rates based on the estimates from the spatial error model. In each case, explicitly taking the error dependence into account results in a slower estimated annual rate of convergence than that based on the ordinary least squares estimate in Table 2. The pattern of a faster rate in the first relative to the second period is, however, repeated in the spatial error estimates.

Table 3. Spatial dependence models

Model specification	AIC[1]	β (p-value)[2]	β, λ, ζ,[3] p-value	LM test,[4,5] p-value
1929–94				
Spatial error (ML)	-104.014	-0.695 (0.000)	0.158	0.287
Spatial lag (ML)	-102.777	-0.641 (0.000)	0.087	0.454
Cross regressive (OLS)	-101.173	-0.661 (0.000)	0.288	0.029
1929–45				
Spatial error (ML)	-124.740	-0.399 (0.000)	0.000	0.665
Spatial lag (ML)	-119.505	-0.338 (0.000)	0.002	0.146
Cross regressive (OLS)	-111.847	-0.370 (0.000)	0.155	0.000
1946–94				
Spatial error (ML)	-106.038	-0.499 (0.000)	0.004	0.483
Spatial lag (ML)	-105.395	-0.414 (0.000)	0.002	0.916
Cross regressive (OLS)	-97.542	-0.465 (0.000)	0.176	0.000

Convergence rates based on spatial error (ML) estimates

	Convergence rate (θ)
1929–94	0.018
1929–45	0.032
1946–94	0.014

Notes: 1. Value of the Akaike Information Criterion.
2. Estimate for β and its p-value.
3. P-value for the spatial coefficient.
4. P-value for the Lagrange Multiplier test for the alternative model (spatial error or spatial lag).
5. Moran's I test of spatial dependence for the cross regressive model.
6. The convergence rate θ is obtained using $\theta = \ln(\beta + 1)/-k$, where k is the number of years in the period.

Structural change and spatial dependence

While the results in Tables 2 and 3 provide indications of different convergence rates in the two sub-periods, the extent to which formal inference regarding this structural change is sensitive to the presence of spatial error autocorrelation has been ignored in the previous literature. In Table 4, a seemingly unrelated regression (SUR) specification is estimated with each of the two sub-periods treated as a separate equation with allowance for cross-equation error covariance. Based on maximum likelihood estimation of the SUR (ML-SUR), several findings emerge. First, the ML-SUR estimates of the convergence parameters in each period are larger than the OLS estimates reported in Table 2. This implies a lower rate of convergence for the ML-SUR estimates for both periods. At the same time, a Wald test on the stability of the convergence parameter across these equations is rejected at $p = 0.10$, which is in agreement with the casual interpretation behind the OLS results in Table 2, namely, more rapid convergence in the first period. However, there is also very strong evidence of spatial error dependence in the two equations as is indicated by the Lagrange Multiplier test at the bottom of Table 4. Again, the diagnostics point to the error model as the more appropriate specification.

Table 5 reports the results from the estimation of a spatial SUR (ANSELIN, 1988) which extends the traditional SUR to allow for spatial autocorrelation in

Table 4. Seemingly unrelated regression tests of structural change

Variable	SUR-ML	Standard deviation	t
Constant2945	4·233	0.243	17·436
Income29	− 0·425	0·029	− 14·888
Constant4694	5·709	0·471	12·122
Income46	− 0·534	0·052	− 10·283
R^2 0·8354			
Cross-equation error covariance matrix			
0·526*10-2	− 0.122*10-2		
− 0.122*10-2	0·708*10-2		
Wald test on coefficient homogeneity across equations			
$\chi^2_{(1)}$	2·294 p-value	0·086	
Spatial dependence tests			
Lagrange Multiplier Error	$\chi^2_{(1)}$	19·361 p-value	6·2*10-5
Lagrange Multiplier Lag	$\chi^2_{(1)}$	18·906 p-value	7·8*10-5

Table 5. Spatial seemingly unrelated regression tests of structural change

Variable	SUR-ML error	Standard deviation	t
Constant2945	4·020	0·451	8·934
Income29	− 0·400	0·053	− 7·587
ζ	0·606	0·122	4·966
Constant4694	5·471	1·217	4·496
Income46	− 0·508	0·134	− 3·792
ζ	0·465	0·149	3·120
R^2 Buse	0·766		
Cross-equation error covariance matrix			
0·36*10-2	0·04*10-2		
0·04*10-2	0·056*10-2		
Wald test on coefficient homogeneity across equations			
$\chi^2_{(1)}$	0·687 p-value	0·407	

the errors of each sub-period equation, while at the same time permitting cross-temporal covariance between the errors from the two equations. The spatial SUR estimates of the parameters on starting income are significant and larger than the respective ML-SUR estimates in both periods, implying a slower rate of convergence than both the ML-SUR and OLS estimates. In addition, the spatial error coefficients are significant in both periods, while the Wald test on the stability of the starting income coefficient is no longer significant. This suggests that the indications of structural change in the rate of convergence based on the traditional SUR approach are misleading due to the presence of spatial autocorrelation in both sub-periods.

Spillover effects in the convergence process

Overall, the results in Tables 2–5 provide strong evidence of spatial effects in the unconditional convergence model widely applied in the literature. Specifically, the spatial error model appears to be the more appropriate specification, over the entire sample period as well as for the two sub-samples. There are several implications of the spatial error specification for the convergence hypothesis. The first concerns a comparison of the implied rates of convergence from the original unconditional model of Table 2 against the implied rates from the spatial error models reported at the bottom of Table 3. In the longer period, the estimated convergence rates are virtually identical between the original and error specifications while, in the two sub-samples, the effect of explicitly taking the error dependence into account is to slightly lower the estimated rate of convergence. While this seems to suggest only a modest role for spatial effects in the convergence process, consideration of the second implication reveals otherwise.

The second implication follows from the properties of the spatial error model as a data generating process detailed above. The presence of significant spatial error dependence results in the random shocks to a specific state being propagated throughout the nation. This is illustrated in Fig. 7 where we introduce a shock to the error term for the state of Missouri and substitute the maximum likelihood estimates of the spatial error model coefficients into equation (8) to estimate the degree of spatial spill-over.[14] As expected, the introduction of the shock has the largest relative impact on Missouri where the estimated growth rate over the 1929–45 period is 22·2% higher relative to the estimate without the shock. However, there is a clear spatial pattern to the propagation of this shock to the other states. The immediate neighbouring states have their predicted growth rates increased by between 1% and 5% due to the spill-over from the Missouri shock, while the magnitude of the shock spill-over dampens as the focus moves away from these central states.

The presence of spatial error dependence as depicted in Fig. 7 implies that movements away from some steady state equilibrium may not be a function of state-specific shocks alone, but instead the possibility now exists for a complex set of shock spill-overs. Given the prominent role of temporal shocks in the recent convergence literature, we feel that our results warrant that similar attention be given to the geographical nature of these shocks. Examination of the interaction between the temporal and spatial dimensions of shocks to individual states remains an important area for future study.

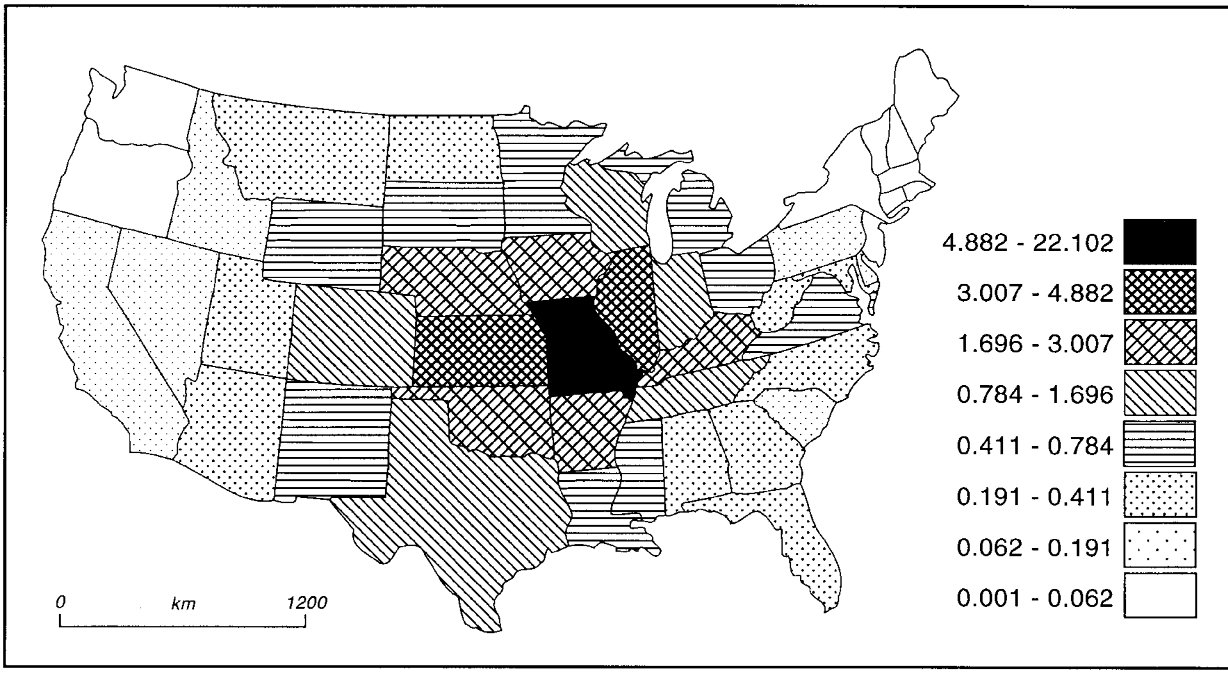

Fig. 7. Percentage change in income growth rate due to spillover of shock to Missouri, 1929–45

CONCLUSION

In this paper, we have provided new insights as to the nature of regional income convergence patterns in the US over the post 1929 era. Our empirical strategy was based on recent developments in exploratory spatial data analysis as well as an explicit spatial econometric perspective. While our results corroborate previous findings on the general pattern of regional income convergence for the US, we are able to provide precise insights as to the geographical dimensions of state income growth as well as new evidence on the role of spatial effects in the formal econometric analysis of regional income convergence.

The application of exploratory spatial data analysis methods revealed strong evidence of spatial autocorrelation in the levels of state per capita incomes over the sample period. We showed that the strength of the spatial autocorrelation in the state incomes was strongly associated with the dispersion of state incomes. We found that the state income growth rates also displayed a great deal of spatial autocorrelation. This suggests that, while states may be converging in relative incomes, they do not do so independently but rather tend to display movements similar to their regional neighbours.

Our confirmatory analysis revealed that the traditional Baumol specification is misspecified due to the presence of strong spatial error dependence. This implies that the finding of spatial autocorrelation in the growth rates based on the univariate tests is not an artifact of the convergence relationship since there remains strong spatial dependence after conditioning on the initial incomes. The presence of spatial error autocorrelation also provides an avenue for random shocks to individual states to not only move that state away from its steady state equilibrium, but to propagate throughout the system of states, thereby complicating the transitional dynamics of the overall convergence process. We also find evidence that previous econometric results indicating the presence of structural change in the rate of regional income convergence for the US had ignored spatial error autocorrelation. When we take the spatial dependence into account, there is no longer any evidence of a structural break in the convergence process over the sample period.

Our results are important in that they represent the first detailed evidence on the role of spatial effects in a regional income convergence study. We have also outlined an initial set of explicit spatial econometric models that can be applied to studies of regional income convergence in other contexts. We hope that this will stimulate others to pursue extensions of these models, perhaps to more fully integrate the spatial and temporal dimensions of the data underlying regional convergence studies.

Acknowledgements – We thank Luc Anselin, Roger Bolton, Jim Gerber, Art Getis, Michael Greenwood, Geoffrey Hewings, Mike Jerrett, the editor and an anonymous referee for very helpful comments. Any errors or omissions remain our responsibility.

NOTES

1. The literature makes a distinction between conditional and absolute (unconditional) convergence, with the former pertaining to the partial correlation of the growth

rate and initial level after controlling for a number of additional variables reflecting differences in equilibrium wages and technologies. Because differences in these variables are likely to be minor across US states (BARRO and SALA-I-MARTIN, 1992) our study focuses on absolute or unconditional convergence.

2. CHATTERJI, 1992, raises similar criticisms of β-convergence.
3. Although CARLINO and MILLS, 1996a, argue that both time-series and cross-sectional tests are necessary for convergence, their approach is based on a largely time-series perspective.
4. Because this framework requires a 'leader' in the sense of an economy with the highest income throughout the study period, it is not applicable to the US system.
5. The source for our data is US BUREAU OF ECONOMIC ANALYSIS, 1996.
6. A similar pattern of σ-convergence is reported for regional per-capita earnings in CARLINO and MILLS, 1996a.
7. All computations were carried out using the SpaceStat software packages (ANSELIN, 1995).
8. The role of the spatial weights matrix is to introduce the notion of a neighbourhood set for each state. Because the determination of a set of neighbours is not without some arbitrariness, we also utilized three alternative definitions to define our weights matrices, which generated results that were very similar to those based on the simple contiguity matrix. These include two other binary matrices and were obtained from using a distance threshold to define a state's neighbourhood set. DC1 uses the first quartile of all state-to-state distances to define states as neighbours, while DC2 uses the second-quartile distance to define the neighbours. Finally, ID1 is a general weights matrix where, for pairs of states separated by less than the first quartile distance, the elements are set equal to the inverse of the squared distances between the states, and for all other pairs the elements are set to zero. For a detailed discussion of the impacts of the choice of a spatial weights matrix in econometric analyses, see FLORAX and REY, 1995.
9. For details on the assumptions underlying the Moran's I statistic, see CLIFF and ORD, 1973, 1981; UPTON and FINGLETON, 1985.
10. The state abbreviations used in Figs. 2, 3 and 6 are defined in Table 1.
11. For further discussion of the properties of local spatial autocorrelation statistics and their application, see GETIS and ORD, 1996.
12. We also implemented and tested a number of models to deal with spatial heterogeneity. However, these models performed poorly relative to the spatial dependence models.
13. The Akaike Information Criterion (AIC) corrects the log likelihood function for overfitting and is a valid measure for comparisons of models with different numbers of explanatory variables (as is the case here). Formally: $AIC = -2L + 2K$, where L is the value of the log likelihood function and K is the number of variables. The best fitting model is the one with the lowest value for the AIC. For further discussion see ANSELIN, 1995.
14. The shock is set equal to twice the standard error of the estimated spatial error specification. We introduce the shock to Missouri because it is close to the centre of the nation and allows for a complete view of the spill-over pattern.

REFERENCES

ABRAMOVITZ M. (1986) Catching up, forging ahead, and falling behind, *J. Econ. Hist.* **46**, 385–406.

AMOS O. M. JR (1988) Unbalanced regional growth and regional income inequality in the latter stages of development, *Reg. Sci. Urban Econ.* **18**, 554–66.

AMOS O. M. JR (1989) An inquiry into the causes of increasing regional income inequality in the United States, *Rev. Reg. Studies* **19**, 1–12.

ANSELIN L. (1988) *Spatial Econometrics: Methods and Models.* Kluwer, Dordrecht.

ANSELIN L. (1993) The Moran scatterplot as an ESDA tool to assess local instability in spatial association, GISDATA Specialist Meeting on GIS and Spatial Analysis, Amsterdam.

ANSELIN L. (1995) Local indicators of spatial association-LISA, *Geogr. Analysis* **27**, 93–115.

ANSELIN L. and BERA A. (1997) Spatial dependence in linear regression models, in ULLAH A. and GILES D. (Eds) *Handbook of Applied Economic Statistics.* Marcel Dekker, New York.

ANSELIN L., BERA A., FLORAX R. J. G. M. and YOON M. (1996) Simple diagnostic tests for spatial dependence, *Reg. Sci. Urban Econ.* **26**, 77–104.

ANSELIN L. and FLORAX R. J. G. M. (Eds) (1995) *New Directions in Spatial Econometrics*, Springer, Berlin.

ANSELIN L. and REY S. J. (1991) Properties of tests for spatial dependence in linear regression models, *Geogr. Analysis* **23**, 112–31.

ANSELIN L. and REY S. J. (1997) Introduction to the special issue on spatial econometrics, *Int. Reg. Sci. Rev.* **20**, 1–7.

ARMSTRONG H. W. (1995) Convergence among regions of the European Union, 1950–1990, *Pap. Reg. Sci.* **74**, 143–52.

BARRO R. J. and SALA-I-MARTIN X. (1991) Convergence across states and regions, *Brookings Pap. Econ. Activity*, no. 1, pp. 107–82.

BARRO R. J. and SALA-I-MARTIN X. (1992) Convergence, *J. Pol. Econ.* **100**, 223–51.

BAUMOL W. (1986) Productivity growth, convergence and welfare: what the long run data show, *Am. Econ. Rev.* **76**, 1,072–85.

BERNARD A. and DURLAUF S. (1995) Convergence in international output, *J. Appl. Econ.* **10**, 1,072–85.

BERNARD A. and DURLAUF S. (1996) Interpreting tests of the convergence hypothesis, *J. Econometrics* **71**, 161–73.

BERNARD A. and JONES C. (1996a) Productivity and convergence across US states and industries, *Empirical Econ.* **21**, 113–35.

BERNARD A. and JONES C. (1996b) Productivity across industries and countries: time series theory and evidence, *Rev. Econ. Statist.* 78, 135–46.

BERNARD A. and JONES C. (1996c) Comparing apples to oranges: productivity convergence and measurement across industries and countries, *Am. Econ. Rev.* 86, 1,216–38.

BRAUN D. (1991) Income inequality and economic development, *Soc. Sci. Quart.* 72, 520–36.

CARDENAS M. and PONTON A. (1995) Growth and convergence in Colombia: 1950–1990 *J. Develop. Econ.* 47, 5–37.

CARLINO G. and MILLS L. (1993) Are US regional incomes converging?, *J. Monetary Econ.* 32, 335–46.

CARLINO G. and MILLS L. (1996a) Testing neoclassical convergence in regional incomes and earnings, *Reg. Sci. Urban Econ.* 26, 565–90.

CARLINO G. and MILLS L. (1996b) Convergence and the US states: a time-series analysis, *J. Reg. Sci.* 36, 597–616.

CASETTI E. (1972) Generating models by the expansion method, *Geogr. Analysis* 4, 81–91.

CHATTERJI M. (1992) Convergence clubs and endogenous growth, *Oxf. Rev. Econ. Policy* 8, 57–69.

CHATTERJI M. and DEWHURST J. H. LL (1996) Convergence clubs and relative economic performance in Great Britain: 1977–1991, *Reg. Studies* 30, 31–40.

CLIFF A. and ORD J. (1973) *Spatial Autocorrelation.* Pion, London.

CLIFF A. and ORD J. *Spatial Processes, Models and Applications.* Pion, London.

COUGHLIN C. C. and MANDELBAUM T. B. (1988) Why have state per-capita incomes diverged recently?, *Rev. Fed. Res. Bank of St Louis* 70, 24–36.

COULOMBE S. and LEE F. C. (1995) Convergence across Canadian provinces, 1969 to 1991, *Can. J. Econ.* 28, 886–98.

CROWN W. H. and WHEAT L. F. (1995) State per capita income convergence since 1950: sharecropping's demise and other influences, *J. Reg. Sci.* 35, 527–52.

DE LONG B. (1988) Productivity growth, convergence, and welfare: comment, *Am. Econ. Rev.* 78, 1,138–59.

EASTERLIN R. (1960a) Interregional differences in per capita income, population and total income, 1840–1950, in NATIONAL BUREAU OF ECONOMIC RESEARCH *Trends in the American Economy in the Nineteenth Century.* Princeton University Press, Princeton, NJ.

EASTERLIN R. (1960b) Regional growth of income, in KUZNETS S., MILLER A. and EASTERLIN R. (Eds) *Population Redistribution and Economic Growth in the United States, 1870–1950.* American Philosophical Society, Philadelphia.

FAN C. C. and CASETTI E. (1994) The spatial and temporal dynamics of US regional income inequality, 1950–1989, *Ann Reg. Sci.* 28, 177–96.

FLORAX R. J. G. M. and REY S. J. (1995) The impacts of misspecified spatial interaction in linear regression models, in ANSELIN L. and FLORAX R. J. G. M. (Eds) *New Directions in Spatial Econometrics.* Springer, Berlin.

GETIS A. (1990) Screening for spatial dependence in regression analysis, *Pap. Reg. Sci.* 69, 69–81.

GETIS A. (1995) Spatial filtering in a regression framework, in ANSELIN L. and FLORAX R. J. G. M. (Eds) *New Directions in Spatial Econometrics.* Springer, Berlin.

GETIS A. and ORD J. (1996) Local spatial statistics: an overview, in LONGLEY P. and BATTY M. (Eds) *Spatial Analysis: Modeling in a GIS Environment.* GeoInformation International, Cambridge, MA.

JONES C. (1997) On the evolution of the world income distribution, *J. Econ. Perspectives* 11, 19–36.

KRUGMAN P. (1987) The narrow moving band, the Dutch disease, and the competitive consequences of Mrs Thatcher, *J. Develop. Econ.* 45, 1–28.

KUZNETS S. (1955) Economic growth and income inequality, *Am. Econ. Rev.* 45, 1–28.

MALLICK R. and CARAYANNIS E. (1994) Regional economic convergence in Mexico, *Growth & Change* 25, 325–34.

MANKIW N., ROMER D. and WEIL D. (1992) A contribution to the empirics of economic growth, *Quart. J. Econ.* 107, 407–37.

QUAH D. (1992) International patterns of growth: I, persistence in cross-country disparities, London School of Economics.

QUAH D. (1993a) Galton's fallacy and tests of the convergence hypothesis, *Scand. J. Econ.* 95, 427–43.

QUAH D. (1993b) Empirical cross-section dynamics in economic growth, *Europ. Econ. Rev.* 37, 426–34.

ROWLEY T., REDMAN J. and ANGEL J. (1991) *The Rapid Rise in State Per Capita Income Inequality in the 1980s: Sources and Prospects.* US Department of Agriculture, Washington, DC.

UPTON G. and FINGLETON B. (1985) *Spatial Data Analysis by Example*, Vol. 1. Wiley, New York.

US BUREAU OF ECONOMIC ANALYSIS (1996) *Regional Economic Information System, 1964–94* (CD-ROM). US Department of Commerce, Washington, DC.

VOHRA R. (1996) How fast do we grow?, *Growth & Change* 27, 47–54.

WILLIAMSON J. (1965) Regional inequality and the process of national development, *Econ. Develop. & Cultural Change* 4, 3–47.