Spatial Economic Analysis

ISSN: 1742-1772 (Print) 1742-1780 (Online) Journal homepage: http://www.tandfonline.com/loi/rsea20

Spatial Growth Regressions: Model Specification, Estimation and Interpretation

James P. Lesage & Manfred M. Fischer

Spatial Economic Analysis, Vol. 3, No. 3, November 2008

Routledge
Taylor & Francis Group

Spatial Growth Regressions: Model Specification, Estimation and Interpretation

JAMES P. LeSAGE & MANFRED M. FISCHER

(Received November 2007; accepted May 2008)

ABSTRACT *We attempt to clarify a number of points regarding use of spatial regression models for regional growth analysis. We show that as in the case of non-spatial growth regressions, the effect of initial regional income levels wears off over time. Unlike the non-spatial case, long-run regional income levels depend on: own region as well as neighbouring region characteristics, the spatial connectivity structure of the regions, and the strength of spatial dependence. Given this, the search for regional characteristics that exert important influences on income levels or growth rates should take place using spatial econometric methods that account for spatial dependence as well as own and neighbouring region characteristics, the type of spatial regression model specification, and weight matrix. The framework adopted here illustrates a unified approach for dealing with these issues.*

Régressions de croissance spatiale: spécification de modèles, estimation et interprétation

RÉSUMÉ *Nous efforçons de clarifler un certain nombre de questions concernant I'utilisation de modéles de regression spatiale pour l'analyse de l'expansion régionale. Nous démontrons que, tout comme dans le cas de régressions non spatiales de la croissance, l'effet initial des niveaux de revenus régionaux finit par s'estomper. Contrairement au cas non spatial, le niveaux de revenus régionaux à long terme sont tributaires: des caractéristiques de notrepropre région et de celles des régions environnantes; de la structure de connectivité spatiale des régions; et de la force de la dépendance spatiale. En conséquence, la recherche de caractéristiques régionales exerçant une grande influence sur les niveaux de revenus ou les taux de croissance doit être effectuée enfaisant usage de méthodes économétriques spatiales tenant compte à lafois de la dépendance spatiale et des caractéristiques de la région en question et des régions environnantes; du type de spécification du modéle de régression spatial; et de la matrice de ponderation. Le cadre adopté ici illustre line méthode unifiée pour aborder ces questions.*

Regresiones de crecimiento espacial: especificación, estimación e interpretación de modelo

RESUMEN *Intentamos clarificar una serie de puntos relacionados con el uso de modelos de regresión espacial para el análisis del crecimiento regional. Mostramos que, como en el caso de regresiones de*

James P. LeSage (to whom correspondence should be sent), Fields Endowed Chair in Urban and Regional Economics from McCoy Endowed Chair, McCoy College of Business Administration, Department of Finance and Economics, Texas State University, San Marcos, TX 78666, USA. Email: jlesage@spatial-econometrics.com. Manfred M. Fischer, Chair for Economic Geography, Institute for Economic Geography and GIScience, Vienna University of Economics and Business Administration, A-1090 Vienna, Austria. Email: manfred.fischer@wu-wien.ac.at

ISSN 1742-1772 print; 1742-1780 online/08/030275-30 DOI: 10.1080/17421770802353758

crecimiento no espacial, el efecto de niveles de ingresos regionales iniciales desaparece con el tiempo. A diferencia del caso no espacial, los niveles de ingresos regionales a largo plazo dependen de: las características de la propia región así como también de las regiones vecinas, la estructura de conectividad espacial de las regiones, y la fuerza de la dependencia espacial. Al ser así, la búsqueda de características regionales que tengan marcadas influencias sobre los niveles de ingresos o las tasas de crecimiento, debería usar métodos espaciales econométricos que expliquen la dependencia espacial, así como también las características propias de la región y de las regiones vecinas, el tipo de especificación de modelo espacial de regresión y la matriz ponderada. El marco que se ha adoptado aquí mostró un enfoque unificado para tratar estos temas.

Keywords: *Model uncertainty; Bayesian model averaging; Markov chain Monte Carlo model composition; spatial weight structures*

JEL classification: C11*;* C21*;* 047*;* 052*;* R11

1. Introduction

Regional economic growth and convergence is a topic that has attracted a lot of attention in recent years. Research on this subject has developed in different directions, but empirical research has focused predominantly on investigating beta-convergence, namely running what are known as cross-sectional growth regressions. Growth theories are not sufficiently explicit about which specific factors underlie the data-generating process for growth regressions, so researchers are faced with a dilemma regarding the large number of potential regressors. There is a trade-off between arbitrary selection of a small subset of variables which may give rise to omitted variables bias, and introduction of a large set of variables that will tend to increase the dispersion of the estimated coefficients, making it difficult to identify important factors. An additional complication is spatial dependence that has for the most part been ignored in this literature, which complicates the task of finding appropriate measures of factors that influence economic growth.

Typically a sequence of tests is performed with the aim of selecting a single best model that excludes irrelevant variables. This approach ignores *model uncertainty* which arises in our spatial regression model from two sources. One aspect of model uncertainty is the appropriate spatial weight matrix describing connectivity between regions used to specify the structure of spatial dependence. The second aspect of model uncertainty arises from variable selection, which sequential testing procedures ignore (Koop, 2003). As is typical in all regression models, we are also faced with *parameter uncertainty*. Durlauf (2001), Sala-i-Martin *et al.* (2004) as well as Fernández *et al.* (2001a, b) point to a Bayesian framework that has been labelled Markov chain Monte Carlo model composition (MC^3) in conjunction with Bayesian model averaging that can accommodate both model and parameter uncertainty in a straightforward and formal way.

While the focus of the non-spatial growth regression literature has been on model and parameter uncertainty, these studies ignore important spatial spillover effects that arise from changes in own region characteristics. Spillovers could be important from a policy perspective since they may create a divergence between the incentives of regional officials and those of supra-regional entities, e.g. national or EU officials. For example, if the Industrial specialization of a region exerts a small positive impact on income growth or income levels but a larger cumulative negative impact on all neighbouring regions, then regional officials have an incentive to promote specialization to the detriment of society at large.

Conventional growth regressions assume that regional observations are independent, but there is a growing consensus that regional income growth rates exhibit spatial dependence. For example, Abreu *et al.* (2004) categorize over 50 growth regression studies, many of which rely on spatial regression methods. One benefit of these methods that has not been exploited is the ability to quantify the magnitude of direct and indirect effects of changing regional characteristics on own region and other region income.

As in the case of non-spatial growth regressions, we show that the effect of initial regional income levels wears off over time for spatial regression models. This leaves us with a situation where regional characteristics are the primary long-run determinants of regional income levels. However, in contrast to non-spatial growth regressions, we demonstrate that long-run steady-state regional income will depend on: own region and neighbouring region characteristics, the spatial connectivity structure of the regions, and the strength of spatial dependence. Given this, the search for regional characteristics that exert important influences on income levels or growth rates should take into account spatial dependence as well as own and neighbouring region characteristics, the type of spatial regression model specification and weight matrix used. The framework adopted here illustrates a unified approach for dealing with these issues.

To deal with model uncertainty regarding explanatory variables and spatial weight structures, we develop and apply an extension of the framework set out in LeSage & Parent (2007) for MC^3 spatial regression models to include model uncertainty regarding the spatial weight matrix and characteristics of neighbouring regions. Spatial growth regression models produce estimates and inferences that are conditional on both the particular weight matrix used to specify which observational units (regions) are linked as well as the set of explanatory variables employed. Selection of an appropriate spatial weight matrix and explanatory variables are central to the analysis of growth empirics and substantive interpretation of the research. Competing specifications are usually non-nested alternatives so that conventional statistical procedures such as the likelihood ratio tests are inappropriate.

An additional source of model uncertainty arises from competing spatial regression specifications. For example, the study by Abreu *et al.* (2004) points to studies that model spatial dependence using a spatial lag of the dependent variable growth rates, while others model the disturbance process as following a spatial autoregressive process, and still others attempt to accommodate spatial dependence in both the growth rates as well as disturbances and explanatory variables. This study resolves the issue regarding the appropriate spatial regression model to be employed using results from Pace & LeSage (2008). They show that spatial dependence in the disturbances of an ordinary least-squares regression model in the presence of an omitted variable that exhibits correlation with an included variable leads to the data-generating process for a model that has been labelled aspatial Durbin model (SDM). This result is independent of any economic theoretical justification in that it rests entirely on the plausibility of a conjunction of two circumstances that seem likely to arise in applied spatial growth regression modelling of regional data samples. We provide details regarding this in Section 2.1.

The remainder of the paper is organized as follows. Section 2 introduces the cross-section growth regression framework along with relevant methodology to deal with model uncertainty in spatial growth regressions. Section 3 applies the methodology to a sample of 255 NUTS 2 regions that covers 25 European countries, and produces estimates and inferences based on models averaged using posterior model probabilities. Some conclusions can be found in the last section.

2. A Unified Approach to the Spatial Growth Regression Model Specification

In Section 2.1 we provide a theoretical motivation for use of the SDM specification based on work by Pace & LeSage (2008). Specifics relating the SDM model to non-spatial growth regressions as well as theoretical implications are set out in Section 2.2. We show that a spatial regression model leads to long-run regional income levels that depend on: own region and neighbouring region characteristics, the spatial connectivity structure of the regions, and the strength of spatial dependence. Issues related to the interpretation of results from our model are discussed in Section 2.3. This includes a discussion of direct and indirect effects that arise from changes in regional characteristics on own region and other region income levels. We quantify these using measures proposed by Pace & LeSage (2008). Section 2.4 describes Bayesian MC^3 model comparison methods. These provide a unified approach to two important model specification issues that arise in spatial growth regression models, namely the appropriate spatial weight matrix to be employed and appropriate explanatory variables. We describe an extension to the approach of LeSage & Parent (2007) that considers alternative models based on different explanatory variables that include comparison of models based on alternative spatial weight matrices as well as explanatory variables.

2.1. Motivation for the Spatial Durbin Model

The SDM in (1) provides a generalization of the conventional growth regression model. The dependent variable y represents an n by 1 vector of observed income growth rates and the n by k matrix X contains k explanatory variables excluding the intercept vector, represented by ι:

$$y = \rho W y + \alpha \iota + X\beta + WX\gamma + \varepsilon. \tag{1}$$

The matrix W is an n by n non-stochastic, non-negative spatial weight matrix. The elements of W are used to specify the spatial dependence structure among the observations. If observation region i is related to observation j, then $W_{ij} > 0$. Otherwise, $W_{ij} = 0$, and the diagonal elements W_{ii} are set to zero as a normalization of the model. The matrix is also normalized to have row-sums of unity, so the 'spatia lag vector' Wy in the model contains a linear combination of growth rates from related regions (those identified by $W_{ij} > 0$). This variable vector captures spatial dependence in y, with the scalar parameter ρ providing a measure of influence for related regions' growth rates on the growth rate of region i. This parameter must take on values less than one, and in spatial growth regressions we would expect to see positive spatial dependence indicating that regional growth rates are positively related to a linear combination of those from related regions. At times we will refer to related regions as 'neighbours' in the sequel, but do not mean to convey map-based contiguity relations, but a more general sense of relatedness.

As already noted, one focus of our analysis is a comparison of varying approaches to defining the set of related regions that should be used to form the matrix W.

We note that W can be non-symmetric, reflecting asymmetry in the weight importance of the relation between regions i and j. The matrix WX represents a linear combination of explanatory variables from related regions, which includes the initial period level of income that is a standard part of the explanatory variable set used in growth regressions. It is conventional to use initial period explanatory variable values in the matrix X to avoid simultaneity and to model initial period regional characteristics as endowments that explain variation in future regional growth rates. The model also includes an n by 1 normally distributed, constant variance disturbance vector, $\varepsilon \sim N(0, \ \sigma_{\varepsilon}^2)$.

In time series models, lagged values of the dependent variable are often included to account for missing explanatory variables. A similar motivation can be used for spatial lags of the dependent variable. This is important for the case of growth regression models since numerous authors have relied on ad hoc statistical tests that suggest a model involving no spatial lags of the dependent variable (see Abreu *et al.,* 2004).

Our motivation for use of the model in (1) is independent of any economic theoretical justification in that it rests entirely on the plausibility of a conjunction of two circumstances that seem likely to arise in applied spatial growth regression modelling of regional data samples. One of these is spatial dependence in the disturbances of an ordinary least-squares regression model. The second circumstance is the existence of an omitted explanatory variable {or variables) that exhibits non-zero covariance with a variable (or variables) included in the model.

With regard to the first circumstance, a nearly universal finding from the growth regression literature is that spatial dependence exists in the residuals from least-squares models (see Abreu *et al.*, 2004). The second circumstance is that a spatially dependent omitted variable exists that is correlated with an included variable. Growth regression models include the (log) initial period level of the dependent variable whose growth rates we are analysing, and spatial dependence is a widely observed phenomenon for variables such as: per capita income levels, employment, and population variables used in the growth regression literature. Omitted variables are also likely to characterize empirical implementations of regional growth regressions, since sample data for measuring numerous factors that may play an important role in economic growth are often limited. It is also the case that these omitted (regional) variables would likely exhibit spatial dependence as well as correlation with at least one of the included variables. In brief, we argue that the conjunction of these two circumstances is highly plausible for the case of regional growth regression analysis.

We let y represent the dependent variable, and x represent a single explanatory variable vector that is included in the model, with z being another vector that will play the role of an excluded explanatory variable. For concreteness, we can let y represent regional income growth rates, x reflect human capital (measured by educational attainment) and z represent propensity for interregional trade, or net commodity flows between regions (for which we have no observed regional sample data information). Consider a situation where the omitted explanatory variable vector z exhibits zero covariance with the vector x, but follows the spatial autoregressive process shown in (3). This leads to a situation where the disturbances from our non-spatial regression relationship exhibit spatial dependence as shown in (4):

$$y = x\beta + z, \tag{2}$$

$$z = \rho Wz + \varepsilon, \tag{3}$$

$$y = x\beta + (I - \rho W)^{-1}\varepsilon. \tag{4}$$

In (4), ρ is a scalar parameter reflecting the strength of spatial dependence in the process governing the omitted variable z, ε is an n by 1 vector of disturbances distributed $N(0, \sigma_u^2 I_n)$, and W is an n by n spatial weight matrix. It seems intuitively plausible that unobserved latent factors such as interregional commodity flows reflecting the propensity for interregional trade would exhibit spatial dependence of the type assigned to the vector z. It seems unlikely that x (human capital) and the omitted z would both exhibit spatial correlation resulting in covariance between these two variables. If z follows the spatial autoregressive process in (3), then z represents a linear function of the random variable ε. Accordingly, if x and z are correlated, then x is correlated with ε. A simple approach to representing this correlation is to specify that ε depends linearly on x, plus a disturbance term v, as in (5), where the scalar parameter γ and the variance of the disturbance term $v(\sigma_v^2)$ determine the strength of the relation between x and z:

$$\begin{aligned} \varepsilon &= x\eta + v, \\ v &= N(0, \sigma_v^2 I_n). \end{aligned} \tag{5}$$

Correlation between the omitted variable z and the included variable x represents conventional treatment of omitted variables bias, since an excluded variable that is orthogonal to the included variable has no impact. Our model takes the form in (6), which can be transformed to the form shown in (7):

$$y = x\beta + (I - \rho W)^{-1}(x\eta + v), \tag{6}$$

$$\begin{aligned} (I - \rho W)y &= (I - \rho W)x\beta + x\eta + v, \\ y &= \rho Wy + x(\beta + n) + Wx(-\rho\beta) + v, \end{aligned} \tag{7}$$

$$y = \rho Wy + x\beta_1 + Wx\beta_2 + v. \tag{8}$$

This result from LeSage & Pace (2008) demonstrates how a seemingly non-spatial linear regression relationship involving a dependent variable y and explanatory variable x can lead to an SDM that includes spatial lags of both the dependent and explanatory variables. The circumstances required to arrive at this result seem highly plausible for most applied spatial growth analysis.

We note that the spatial error model (SEM) used in many spatial growth studies can arise only if there are no omitted explanatory variables, or if these are not correlated with included explanatory variables, both of which seem highly unlikely circumstances in applied practice. For example, regional information on physical capital is frequently not available and excluded from the set of explanatory variables, whereas human capital measures such as educational attainment are routinely included as explanatory variables in growth regressions. Furthermore, both physical and human capital variables are likely to be correlated, and to exhibit spatial dependence.

We will employ the SDM specification in this study and argue that the conjunction of plausible circumstances likely to arise in applied spatial growth regression modelling make this model specification a natural choice over competing alternatives. We also note that this model nests most models used in the regional growth literature. For example, imposing the restriction that $\beta_2 = 0$ leads to a spatial autoregressive (SAR) model that includes a spatial lag of growth rates from related regions, but excludes these regions' characteristics. Imposing the restriction that $\beta_2 = -\rho\beta_1$ yields the SEM specification noted above. It is interesting that the presence of non-zero η leads to $\beta_1 = \beta + \eta$ so expression (7) suggests that the restriction $\beta_2 = -\rho\beta_1$ is plausible only in situations where there are no omitted variables that exhibit correlation with included variables. Imposing the restriction that $\rho = 0$ leads to a spatially lagged X growth regression model (SLX) that assumes independence between regional growth rates, but includes characteristics from related regions in the form of explanatory variables WX. Finally, imposing the restriction that $\rho = 0$, $\beta = 0$ leads to a non-spatial least-squares growth regression model that assumes that regional growth rates are independent.

2.2. *A Spatial Growth Regression*

A final point relates to the specific functional form employed for the spatial regression model, and its implications for interpreting the coefficient estimates of the model. We contrast non-spatial and spatial growth regressions in this regard.

The non-spatial growth regression takes the form in (9), where T is the number of years between the initial period (0) and final period (t), where we have suppressed the intercept for simplicity:

$$[\ln(y_t) - \ln(y_0)]/T = \phi\ln(y_0) + X_0\beta + \varepsilon_t, \tag{9}$$

$$\ln(y_t) = (1 + T\phi)\ln(y_0) + TX_0\beta + T\varepsilon_t. \tag{10}$$

A key feature of this model is that when $\phi < 0$, dependence of y_{t+q}.on the initial levels y_0 disappears for large q. The time required for this can be analysed using the half life time to convergence suggested by: $\ln(y_{t+q}) = (1 + \phi)^q\ln(y_0)$. Solving for q leads to: $q = \ln(0.5)/ln(1 + \phi) = -\ln(2)/\ln(1 + \phi)$. Of course, we can run either the growth rate regression in (9) or the levels regression in (10) and use our knowledge of T to recover the parameter ϕ needed to determine the speed of convergence. This suggests, that in the long run income levels will be determined by the characteristics in X_0 and the associated parameters β, which has led to interest in finding explanatory variables that exert large and significant influences on the level of income (or equivalently growth rates).

Our spatial SDM generalization of this model is based on the assumption that regional growth rates exhibit spatial dependence because of omitted variables, leading to:

$$\begin{aligned}(I_n - \rho W)[\ln(y_t)] - \ln(y_0)/T &= \phi\ln(y_0) + X_0\beta_1 + WX_0\beta_2 + \varepsilon_t,\\ (I_n - \rho W)\ln(y_t) &= (1 + T\phi)\ln(y_0) - \rho W\ln(y_0) + TX_0\beta_1 + TWX_0\beta_2 + T\varepsilon_t,\\ \ln(y_t) &= \rho W\ln(y_t) + (1 + T\phi)\ln(y_0) - \rho W\ln(y_0) + TX_0\beta_1) + WTX_0\beta_2 + T\varepsilon_t.\end{aligned} \tag{11}$$

This is our SDM model, where the dependent variable represents regional income levels rather than the typical annualized growth rates, and the explanatory variables matrices consist of spatial lags of the initial levels of income, $\ln(y_0)$ as well as the explanatory variables, WX_0.

Like the non-spatial model, this model also has the property that dependence on the initial level of income disappears with the passage of time, which can be seen by expressing (11) as in (12):

$$\ln(y_t) = (I_n - \rho W)^{-1}[(1 + T\phi)I_n - \rho W]\ln(y_0) + (I_n - \rho W)^{-1} TX_0\beta_1 \\ + (I_n - \rho W)^{-1} WTX_0\beta_2 + (I_n - \rho W)^{-1} T\varepsilon_t. \quad (12)$$

The time required for this will be determined by the principal eigenvalue of (ln $-\rho W)^{-1}[(1 + T\phi)I_n - \rho W]$ which equals:[1]

$$\lambda = \frac{1 + \phi - \rho}{1 - \rho}, \\ k = -\ln(2)/\ln(\lambda). \quad (13)$$

Unlike the case of the non-spatial model, the long-run income levels will be determined by the characteristics in X_0, plus those of neighbouring regions reflected by WX_0, as well as the level of spatial dependence captured by the parameter ρ and spatial connectivity structure represented by W. We motivate this with the following development.

Beginning with our model expressed as in (14), we can recursively replace y_0 on the right-hand-side of (14) with: $y_{t+T} = \rho W y_t + Z_0\delta + \varepsilon_{t+T}$ Continuing this for q rounds yields (15) and (17):

$$y_t = [(1 + T\phi)I_n - \rho W)]y_0 + Z_0\delta + \varepsilon_t, \\ Z_0 = (\iota X_0 WX_0), \\ \delta = (\alpha\beta_1\beta_2)', \quad (14)$$

$$y_{t+T_q} = I_n + \rho W + \rho^2 W^2 + \ldots + \rho^q W^q)\ Z_0\delta + G^q W^q y_0 + u, \quad (15)$$

$$G = [(1 + T\phi)I_n - \rho W], \quad (16)$$

$$u = \varepsilon_{t+Tq} + \rho W \varepsilon_{t+T_q-T} + \rho^2 W^2 \varepsilon_{t+T_q-2T} + \ldots + \rho^{q-1} W^{q-1} \varepsilon_t. \quad (17)$$

Note that, $E(u) = 0$ in (17) since $E(\varepsilon_{t+I}) = 0$, $i = 0, \ldots, Tq$. It is also the case that for conventional row-stochastic matrices W, where $|\rho| < 1$ and the maximum eigenvalue of the matrix W is unity, and for stationarity where $1 + T\phi < 1$, the magnitude of $G^{Tq} W^{Tq} y_0$ becomes small for large q.[2]

A consequence of this is that the long-run expectation, which can be interpreted as the steady-state equilibrium, will depend on regional characteristics in X_0 as well as those of neighbours in WX_0 (and associated parameters) and the level of spatial dependence ρ and spatial connectivity embodied in the matrix W:

$$\lim_{Tq\to\infty} E(y_{t+T_q}) = \lim_{Tq\to\infty} (I_n + \rho W + \rho^2 W^2 + \cdots + \rho^q W^q) Z\delta \\ = (I - \rho W)^{-1} Z_0\delta \\ = (I - \rho W)^{-1} (\iota X_0 WX_0)^{\delta},$$

where the asymptotic expansion of the inverse relationship (Debreu & Herstein, 1953) $(I_n - \rho W)^{-1} = I + \rho W + \rho^2 W^2 + \cdots$ was used to arrive at the final result.

This suggests that we should focus our efforts on finding explanatory variables X_0, WX_0 while talcing account of spatial dependence and connectivity. We will see that this also involves consideration of both direct effects that arise from regional characteristics in X_0 as well as indirect or spatial spillover effects that occur in this model and influence the level of regional income.

2.3. Interpreting the Spatial Growth Regression

In our spatial growth regression that includes a spatial lag of the dependent and independent variables, a change in a single explanatory variable in region i has a 'direct impact' on region i as well an 'indirect impact' on other regions $j \neq i$. This result arises from the spatial connectivity relationships that are incorporated in spatial regression models.

Although the spatial connectivity of regions lies at the heart of regional science, this feature of spatial econometric models also increases the difficulty of interpreting the resulting estimates. Pace & LeSage (2008) provide computationally feasible means of calculating scalar summary measures of these two types of impacts that arise from changes in the explanatory variables of our SDM.

The data-generating process for the SDM can be written as in (18):

$$y = \sum_{r=1}^{p} S_r(W)x_r + (I_n - \rho W)^{-1}\iota_n\alpha + (I_n - \rho W)^{-1}\varepsilon, \tag{18}$$

$$S_r = (I_n - \rho W)^{-1}(I_n\beta_r + W\theta_r). \tag{19}$$

The index $r = 1 \ \ldots, p$ so that x_r, is the rth explanatory variable (rth column of X_0), and there are $k = 2p + 1$ explanatory variables. The p by 1 vector β contains the regression parameters associated with the explanatory variables in X_0, and the p by 1 vector θ contains the regression parameters associated with the spatially lagged explanatory variables WX_0. We switch notation from our earlier use of β_1 and β_2 to avoid awkward use of subscripts here, since we wish to reference the rth explanatory variable which has associated coefficients β_r, θ_r.

Given estimates for our SDM model, Pace & LeSage (2008) take up the question of interpreting the impacts that arise from changing a particular explanatory variable. Using (18), they establish that changes in the rth explanatory variable in a spatial regression model have a partial derivative impact on y_i equal to (20), where $S_r(ij)$ refers to the ijth element of the n by n matrix S_r:

$$\frac{\partial y_i}{\partial x_{jr}} = S_r(ij). \tag{20}$$

The standard regression interpretation of estimated parameters as partial derivatives describing the magnitude of changes in y_i that arise from changes in x_{ir} is no longer valid. That is, $\partial y_i/\partial x_{ir} \neq \beta_r$ *for all* $i, r,$ *and* $\partial y_i/\partial x_{ir} \neq 0,$ *for* $j \neq i$ in our SDM model.

In the case of the own derivative for the ith observation region, which Pace & LeSage (2008) label the *direct effect*, this is measured by the i, ith element of S_r. This includes feedback influences that arise as a result of impacts passing through neighbours, and back to the observation itself. To see this, consider that the *i*, *i*th element of the matrix S_r will contain non-zero values on the diagonal that represent the feedback effects. These arise because a region is a neighbour to its neighbour, so changes that impact region *i* will impact its neighbouring regions, and these will in turn exert higher order feedback effects on region *i*. Despite the fact that the main diagonal of the matrix W contains zeros, the main diagonal of higher order matrices W^k that arise in the infinite series expansion representation of the matrix inverse are non-zero. For example, W_{ii}^2 is non-zero to reflect the fact that region *i* is a second-order neighbour to itself, that is a neighbour to its neighbour. This accounts for the feedback effects.

The *indirect effects* that arise from changes in all observations $j = 1, \ldots, n$ of an explanatory variable x_{jr}, $j \neq i$, are found as the sum of the off-diagonal elements of the rows *i* from the matrix $S_{r,}$ for each observation *i*. These are what are commonly thought of as spatial spillovers. Direct plus indirect effects equal the total effect from *ceteris paribus* changes in the variable *r*.

Since the impact of changes in an explanatory variable differ over all observations, Pace & LeSage (2008) propose the following scalar summary measures of these varying impacts.

The *Average Direct effect* is constructed as an average of the diagonal elements of S_r. This measure summarizes the impact of changes in the *r*th variable using an average across the entire sample of regions.

The *Average indirect effect* is constructed using an average of the off-diagonal elements of S_r. The off-diagonal row elements are first averaged, and then an average of these averages is taken.

It should be kept in mind that the scalar summary measures of indirect effects cumulate over all regions, so they would often be larger than the direct effect estimates. While this may seem counterintuitive, the indirect effects falling on any single region would most likely be much smaller than the direct effects. Also, the largest indirect effects would fall on nearby regions. It is the cumulating of the spatial spillovers over all regions that leads to relatively larger indirect than direct effects. We will illustrate the difference between cumulative indirect effects and marginal effects that fall on nearby regions in our application.

The *Average effect* is simply the sum of the direct and indirect effects. This would represent the sum of diagonal plus off-diagonal elements of the matrix S_r, averaged.

We note that these summary measures of the impacts arising from changes in the explanatory variables of the model average over all regions or observations in the sample, as is typical of regression modei interpretations of the parameters β_r. Of course, one could examine direct and indirect impacts for an individual region *i* without averaging, but this would take the form of a 1 by *n* row vector for each region *i* considered. This type of limited analysis can be found in a number of papers, e.g. Anselin & Le Gallo (2006), Kelejian *et al.* (2006), and Dall'erba & Le Gallo (2007).

In addition to providing computationally efficient methods for calculating the scalar summary measures of the *n* by *n* matrix of partial derivatives that arise from changes in be explanatory variables, Pace & LeSage (2008) show how to produce statistical measures of dispersion for these scalar summaries. These allow inferences regarding the statistical significance of the direct, indirect and total impacts that arise from changes in the explanatory variables.

We will use these scalar summary measures to draw inferences regarding the magnitude, sign and significance of the various explanatory variables that appear in our spatial Durbin growth regression model.

The conventional non-spatial growth regression focuses attention on regional characteristics (X_0) that exert an important influence on income levels (or equivalently growth rates). In contrast to the non-spatial growth regression, we must also focus on determining characteristics of neighbouring regions (WX_0) in the context of spatial dependence, where our model includes spatial lags of the dependent and independent variables. In addition, the matrix W employed in our model needs to be considered as part of the model specification. We turn attention to these issues in the next section.

2.4. *Bayesian Model Comparison*

We are interested in comparing models that differ in two regards, namely the spatial weight matrix specification and the set of explanatory variables.

Use of spatial growth regressions requires specifying the non-zero elements in the spatial weight matrix, which determines a neighbourhood set for each row (observation/region) of the matrix W. The conventional approach defines the neighbourhood set using the geographical arrangement of the observations, designating regions as neighbours when they have a border in common (first-order contiguity) or when they are within a given (critical) distance of each other. In this study we constrain the neighbour structure to take the form of an h nearest neighbour matrix. Specification of this type of spatial weight structure involves selecting two parameters: the number of neighbours which we denote h, and the type of distance measure which we label d, so $W = W(h,d)$. In our empirical application, we work with three alternative distance metrics that reflect different aspects of regional connectivity: (1) geodesic distances, (2) road travel time distances for cars, and (3) drive time distances for heavy goods vehicles. The drive time measures of distance reflect economic distance which may introduce additional realism to connectivity. The structure of the road networks, the presence of mountains, rivers, oceans, landlocked areas, national car and lorry speed limits, as well as statutory rest periods for drivers may lead to large differences between geodesic and drive time distances. These differences will lead to variation in the weight matrix specification associated with varying combinations of the parameters h to and d that define our weight matrix. Since spatial regression estimates and inferences are conditional on the weight matrix employed, this specification could have an important influence.

There is a great deal of literature on Bayesian model comparison for non-spatial regression models, where alternative models consist of those based on differing matrices of explanatory variables. For the case of a small number of alternative least-squares regression models, Zellner (1971) sets out the basic Bayesian theory behind model comparison. The approach involves specifying prior probabilities for each model as well as prior distributions for the regression parameters. Posterior model probabilities are then calculated and used for inferences regarding the alternative models based on different sets of explanatory variables.

Work by Fernández *et al.* (2001a, b) considers cases where the number of possible models m is large enough that calculation of posterior probabilities for all models is difficult or unfeasible. A Markov chain Monte Carlo model composition methodology, known as MC^3, proposed by Madigan & York (1995) has gained popularity in the mathematical statistics and econometrics literature (e.g. Raftery *et al.*,1997; Dension *et al.*,1998; Fernández *et al.* (2001a,b).

LeSage & Parent (2007) extend the MC^3 approach to the case of SDMs of the type considered here. However, the approach considers models containing alternative explanatory variables conditional on a single fixed spatial weight matrix. An important aspect of our spatial growth regression models is the spatial weight matrix employed. We extend this approach to include simultaneous comparison of models based on both alternative spatial weight matrices as well as explanatory variables.

For the purposes of this discussion, we designate the SDM as in (21). The parameter h denotes the number of nearest neighbours used to construct the spatial weight matrix W, and the parameter d represents the type of spatial weight matrix. In our applied illustration we consider three different types of spatial weight matrices, one based on lorry (truck) drive time distances between the economic centres of the regions, another based on car travel time distances between these centres and a third based on great circle distances between the regional centres:

$$y = \alpha \imath + \rho W(h, d)y + X\beta + W(h, d)X\theta + \varepsilon. \tag{21}$$

The Bayesian theory behind model comparison involves specifying prior probabilities for each of the m alternative models $M = M_1$, M_2, ..., M_m under consideration, which we label $\pi(M_i)$, $i = 1, \ldots, m$, as well as prior distributions for the parameters $\pi(\eta)$, where $\eta = (\rho,\alpha,\beta,\theta,\sigma,h,d)$. We rely on a prior distribution to define the range of nearest neighbours parameter h, which was set between 1 and 10 in our applied illustration. Inherent in the use of spatial autoregressive models is the notion that the number of relevant neighbours will be limited, resulting in a sparse spatial weight matrix, so selection of an appropriate a priori range should not be difficult in applied practice.

If the sample data are to determine the posterior model probabilities, the prior probA abilities should be set to equal values of $1/m$, making each model equally likely a priori. These are combined with the likelihood for y conditional on ψ as well as the set of models M, which we denote $p(y|\psi, M)$. The joint probability for M, ψ, and y takes the form:

$$p(M, \psi, y) = \pi(M)\pi(\psi|M)p(y|\psi,M). \tag{22}$$

Application of the Bayes rule produces the joint posterior for both models and parameters as:

$$p(M, \psi|y) = \frac{\pi(M)\pi(\psi|M)p(y|\psi,M)}{p(y)}. \tag{23}$$

The posterior probabilities regarding the models take the form:

$$p(M|y) = \int p(M, \psi|y)d\psi, \tag{24}$$

which requires integration over the parameter vector ψ. LeSage & Parent (2007) develop expressions for the marginal posterior in (24) for the SDM model that we will be using here for the case of the parameters h, d fixed. That is, they consider only models that differ in terms of the explanatory variables matrix X in the model, and derivs the log-marginal posterior expressions by analytically integrating out the parameters α, β, θ and σ from (24), resulting in an expression for the log-marginal likelihood that depends on the parameter ρ, conditional on a particular type of weight matrix d and number of nearest neighbours h.

LeSage & Parent (2007) rely on computationally efficient univariate numerical integration over the single parameter ρ, with computational details provided in an appendix to their paper. This procedure converts the log-marginal likelihood to a scalar expression for a given model based on alternative explanatory variables. In our case, their log-marginal likelihood for a given model will be treated as conditional on the type of weight matrix d and the number of neighbours used to construct the weight matrix h. Formally, we can define the vector of parameters $\psi = (\rho, \alpha, \beta, \theta, \sigma)$, and note that this was reduced to only ρ using analytical integration over the parameters $(\alpha, \beta, \theta, \sigma)$. In the approach used by this paper we require integration over the two additional parameters d and h, both of which take on a discrete number of values, making this relatively simple. We can write formally:

$$
\begin{aligned}
p(M|y) &= \int_d \int_h \int_p p^*(M, \rho, h|j)\mathrm{d}\rho,\ \mathrm{d}h, \mathrm{d}d \\
p^*(M, \rho, h, d|j) &= \int_\psi p(M, \alpha, \beta, \theta, \sigma, \rho, h, d|y)\mathrm{d}\psi.
\end{aligned}
\tag{25}
$$

LeSage & Parent (2007) show how the MC^3 method of Madigan & York (1995) can be used to move a Markov chain Monte Carlo sampler through a potentially large model space so it will sample regions of high posterior support. This procedure eliminates the need to consider all possible models by constructing a sampler that explores relevant parts of the very large model space. If we let M denote the current model state of the chain, models are proposed using a neighbourhood, $nbd(M)$ which consists of the model M itself along with models containing either one variable more or one variable less than M. We extend this notion of the model neighbourhood to include models containing the same type of weight matrix (lorry drive or car travel time, or great circle distance) with one neighbour more, or one neighbour less. The proposed model M' is compared to the current model state M using the following acceptance probability:

$$
\min\left[1, \frac{p(M'|y)}{p(M|y)}\right]. \tag{26}
$$

Another equivalent approach to accomplishing integration over the two additional parameters d, and h is simply to treat the log-marginal expression from LeSage & Parent (2007) as reflecting the conditional distribution for the new parameters and rely on the same Metropolis–Hastings procedure for comparing alternative models. This amounts to using an expression $p(M|d, h, y) = \int_\rho(\mathrm{M}|\rho, d, h, y)\mathrm{d}\rho$ in place of $p(M|y)$ and $p(M'|d', h, y)$ or $p(M'|d, h', y)$ in the Metropolis–Hastings accept/reject decision of (26). This notation conveys the fact that alternative model proposals involve not only different matrices of explanatory variables but different spatial weight matrices arising from differing choices of weight matrix types (d) as well as different numbers of nearest neighbours (h).

Use of univariate numerical integration methods described in LeSage & Parent (2007) allows us to construct a Metropolis–Hastings sampling scheme that implements the MC^3 method. A vector of the log-marginal values for the current model M is stored during sampling along with a vector for the proposed model M'.

These are then scaled and integrated to produce the ratio $p(M'|y)/p(M|y)$ in (26) that determines acceptance or rejection of the proposed model.

As in the case of LeSage & Parent (2007), the intercept parameter in the model along with the spatial lag of the dependent variable were included in all models. They argue that this approach holds intuitive appeal since in the absence of any other explanatory variables entering the model we have a first-order spatial autoregressive model involving only an intercept and the spatial lag of the dependent variable.

3. An Application to EU Regions

In this empirical illustration we consider Bayesian model averaging in a pan-European growth context. Section 3.1 describes the sample data for 255 NUTS 2 regions in 25 European countries that covers all of Europe except South East Europe, Cyprus, Malta, Iceland and Liechtenstein. Results from MC^3 the Muypxocedure are reported in Section 3.2, with estimates and associated inferences based on models averaged using posterior model probabilities discussed in Section 3.3. Section 3.4 presents a correct interpretation of the spatial regression parameter estimates that takes the simultaneous feedback nature of the regional growth regression model into account.

3.1. The Sample Data

We use gross value added, GVA, rather than gross regional product (GRP) at market prices as a proxy for regional income. The proxy is measured in accordance with the European System of Accounts (ESA) 1995. Our main data source is Eurostat's Regio database. The data for Norway and Switzerland stem from Statistics Norway (Division for National Accounts) and the Swiss Office Féderal de la Statistique (Comptes Nationaux), respectively. GVA has the comparative advantage of being the direct outcome of variation in factors that determine regional competitiveness. The dependent variable is (the log of) average per capita GVA for the period 1995–2003. The time period is relatively short due to a lack of reliable figures for the regions in Central and Eastern Europe. This comes partly from the change in accounting conventions now used in these countries. But more important, even if estimates of the change in the volume of output did exist, these would be impossible to interpret meaningfully because of the fundamental change of production from a centrally planned to a market system (Fischer & Stirböck, 2006). The observation units are NUTS 2 regions that are adopted by the European Commission for their evaluation of regional growth and convergence processes. Appendix A describes the sample of regions.

We consider $p = 23$ candidate explanatory variables and their spatially lagged forms. All the variables are measured at the beginning of the sample period (i.e. 1995) to avoid endogeneity problems. The variable names and the data sources are depicted in Table 1. There are only very few variables that appear in all or at least most regressions in the literature. One obvious variable is the initial level of income. Most researchers include this variable in their analysis and find it to be significant (this is the conditional convergence effect). Human capital is another variable that is widely considered as a key determinant of economic growth. We measure human capital by the skills of the workforce as given by the level of

Table 1. The variables used in the analysis (measured at the beginning of the sample period and taken in logarithmic form)

Variable	Description
Initial income	Gross value added divided by population 1995. *Source*: Regio database, Eurostat; Statistics Norway and Swiss Office Féderal de la Statistique
Human capital	Skill of the workforce as given by the level of educational attainment of the population (aged 15 and over 1995) with higher education. *Source*: Regio database, Eurostat
Physical capital	Gross fixed capital accumulation. *Source*: Regio database, Eurostat
Output of innovation activities	Measured in terms of the ratio of the number of EPO patent applications to GVA per capita (1995). *Source*: EPO database; Regio database, Eurostat
Specialization measure	Proportion of patents issued in the region's top industry relative all European patents in the same industry (1995), where top industry is defined in terms of terms of the number of patent applications. *Source*: EPO database
Diversity measure	Share of top five 'industries' patents relative to patents in all industries (1995). *Source*: EPO database.
High-technology invention activities	Corporate patent applications in the higl-technology sector (1995), where high technology is defined to include the ISIC sectors of aerospace (ISIC 3845), electronics and telecommunication (ISIC 3832), computers and office equipment (ISIC 3825), and pharmaceuticals (ISIC 3522). *Source*: EPO database
Patent activities	Corporate patent applications (1995). *Source*: EPO database
Regional industry composition	Employment in various industry sectors: agriculture, construction, food–beverages–tobacco, textiles, fuels–chemicals–rubber, electronics, transportation equipment, other manufactures, wholesale–retail trade, hotels–restaurants, transportation–public utilities, finance, and other services. *Source*: Cambridge Econometrics database
Market potential	For a region defined in terms where the size of the regional economy is proxied by GVA, and is the interregional great circle distance. *Source*: GVA data from Regio database, Eurostat
Population density	Population density per square km (1995). *Source*: Regio database, Eurostat Square km
Area	(1995). *Source*: Regio database, Eurostat

educational attainment of the population. We also included gross fixed capital formation as a measure of physical capital.

Any study of regional economic growth is constrained by a shortage of data. Economists have known for decades that intangibles such as innovation and technological change drive the process of growth. It is, however, difficult to find good measures for such intangibles. Despite the inherent difficulties in measuring the effects of technological progress on economic growth we rely on a series of candidate patent-based variables that capture different aspects of the process of innovation and technological change at the regional level. One of these variables is the log of the number of patent applications at the European Patent Office (EPO). This can be considered as a proxy for the output of invention activities in each region. We also considered technology input measures such as R&D expenditures and personnel, but data on these variables were missing for a considerable number of regions in our sample.

There is substantial empirical evidence supporting the role of high-technology firms in technological change and economic growth. We used MERIT'S Concordance Table (Verspagen *et al.*, 1994) between the four-digit ISIC sectors and the 628 patent sub-classes of the International Patent Code (IPC) classification to identify such patents from the universe of European patent applications. High technology is defined to include the ISIC sectors of aerospace (ISIC 3845), electronics-telecommunication (ISIC 3832), computers and office equipment

(ISIC 3825), and pharmaceuticals (ISIC 3522). This information was used to form the high-technology invention activities variable, which represents the log of corporate patent applications in these industry sectors.

Two further variables represent measures of specialization and diversity based on the industries in which each region was engaged in patented invention activities during 1995. These measures mirror similar variables proposed by Glaeser *et al.* (1992), but rely on the industrial composition of patenting activities taking place in 1995 in each region. This type of activity should reflect industries in which the regions are actively engaged in knowledge production, R&D, and innovation. The specialization measure is defined as the proportion of EPO patent applications issued in the top industry divided by the percentage of all patent applications in the European sample in the same industry during 1995. Values of this location quotient greater than one would indicate that the region is more heavily specialized in this industry than the European sample as a whole. The diversity measure was constructed using the share of the top five industries' patents relative to patents in all industries in each region. This provides a measure of how diverse the innovation activities are, with lower numbers reflecting more diversity and higher proportions less diversity. If diversity exerts a positive impact on income growth, we would expect a negative sign for the coefficient associated with this variable.

Additional candidate explanatory variables are included in the regressions with the purpose of accounting for likely differences in technological change. To control for the industrial mix, we follow López-Bazo *et al.* (2004) and consider the logged levels of employment in: agriculture, construction, food–beverages–tobacco, textiles, fuels–chemicals–rubber, electronics, transportation equipment, other manufactures, wholesale–retail trade, hotels–restaurants, transportation–public utilities, finance, and other services. We also include an index of market potential that measures the export demand each region faces given its geographical location and that of its trading partners. The idea that market access is important for regional income goes back to Harris (1954) who argues that the potential demand for goods and services produced in any region depends upon the distance-weighted GRP (in our study: GVA) of all regions. Finally, we follow Fingleton (2001) and consider (log) population density and (log) area as candidate explanatory variables.

Regions with higher population density represent urban agglomerations that contain larger human capital stocks as a repository of knowledge, which provide a boost to innovation creation and adoption and hence to technological progress and economic growth.

3.2. MC^3 *Estimation Results*

Details regarding implementation and results from MC^3 procedures are described in Appendix B. We focus discussion here on results regarding the 'important variables' selected by these procedures. One point is that use of non-spatial regression models in the face of spatial dependence that leads to a model containing-a-spatial lag of the dependent variable results in biased and inconsistent estimates (LeSage & Pace, 2008). This suggests that application of MC^3 procedures to non-spatial regression models would lead to erroneous inferences regarding which variables are important. Examples of this are presented in LeSage & Parent (2007) and LeSage & Pace (2007), so we do not examine this issue here.

The top five models are reported in Table 2, which shows the variables appearing in the five highest posterior probability models, with variables that appear

Table 2. High-probability models

Variable name/models	5	4	3	2	1	Prob.
Initial income	1	1	1	1	1	0.761194
Agricultural employment	0	0	0	0	0	0.056690
Finance employment	1	1	1	1	1	0.303528
Human capital	1	1	1	1	1	0.325770
Population density	1	1	1	1	1	0.326346
Area	1	1	1	1	1	0.326460
W initial level	1	1	1	1	1	0.798958
W construction empl.	1	1	1	1	1	0.312102
W textiles empl.	0	0	0	0	0	0.054712
W wholesale–retail trade empl.	1	0	1	0	0	0.215032
W trans, pub. util. empl.	0	0	0	0	0	0.089836
W other services empl.	0	1	1	1	1	0.052786
W human capital	1	1	1	1	1	0.316578
W population density	1	0	1	1	0	0.077024
W area	0	1	0	0	1	0.065580
Model probabilities	0.029	0.030	0.034	0.037	0.067	
No.of neighbours	5	5	8	8	5	

in each model designated with a '1' and those that do not appear with a '0'. The last column shows the probability that each variable should enter the model based on the frequency of appearance of each variable in the top 1,000 models.[3] To conserve on space, only variables with inclusion probabilities greater than 5% are shown in the table. The bottom row of the table shows the posterior model probability associated with each of these five models.

From the table we see that the initial level of income and its spatial lag appeared in all of the top five models, and over 75% of the top 1,000 models, indicated by the inclusion probabilities of 76.1 and 79.8, respectively.

The other variable that appears in all five top models along with its spatial lag is human capital. Here we see a probability of inclusion for human capital of 32.5% and 31.6% for its spatial lag. The importance of the initial level of income and human capital is consistent with other studies of economic growth in non-spatial settings where these variables also appeared as the most important (e.g. Fernández *et al.*, 2001b).

Population density and area appeared in all five top models, having inclusion probabilities over 30%, but the spatial lags of these variables did not appear in all five top models, and had probabilities of 7.7% and 6.5%, respectively.

The other variables with inclusion probabilities greater than 5% were all industry-level employment variables, reflecting the fact that industrial structure played a somewhat important role in determining the level (and growth) of income. Employment in the agricultural and finance sectors appeared as well as spatial lags involving employment in construction, textiles, the wholesale and retail trade, transportation and public utilities and other services.

3.3. Model Averaged Estimates

The Bayesian solution to model uncertainty involves use of a linear combination of estimates from more than a single model, with the estimates from each model weighted by the posterior model probabilities. For the case of Markov Chain

Monte Carlo (MCMC) estimation this simply involves use of a linear combination of the 'MCMC draws' weighted by the posterior model probabilities. These combined or *model averaged estimates* provide the basis for posterior inference regarding the parameters. Since the *model averaged estimates* reflect estimates arising from alternative models involving different spatial weight matrices, differing numbers of neighbours and different explanatory variables, our inferences embody model uncertainty. This approach is in contrast to conventional methods that condition on a single selected model and ignore model uncertainty which, in turn, can lead to the underestimation of dispersion in the resulting estimates.

Model averaged estimates were constructed based on the alternative sets of explanatory variables identified by the MC^3 procedure. These are presented in Table 3, based on the 500 highest probability models which accounted for 99.77% of the posterior probability mass. As is conventional, the model probabilities were normalized to unity. Posterior means as well as upper and lower 0.01 credible intervals are reported based on the distribution of MCMC draws. The table reports

Table 3. Model averaged estimates

Variables	Lower 01 interval	Posterior mean	Upper 99 interval	Posterior SD
Initial income	0.74286	0.75036	0.75720	0.003151
Agricultural empl.	−0.00078	−0.00045	−0.00011	0.00013
Construction empl.	0.01046	0.01412	0.0177	0.00154
Textiles empl.	−0.00037	−0.00026	−0.00016	0.00004
Hotels, restaurants empl.	0.00044	0.00072	0.00097	0.00010
Tran, public utilities empl.	0.00751	0.00936	0.01118	0.00081
Finance empl.	0.05225	0.05620	0.06035	0.00173
Patents	0.00022	0.00036	0.00051	0.00006
Human capital	0.11784	0.12294	0.12832	0.00220
Higly –technology patents	0.00023	0.00068	0.00110	0.00018
Population density	−0.20935	−0.20199	−0.19478	0.00307
Area	−0.20970	−0.20307	−0.19639	0.00282
Diversity	−0.00681	−0.00465	−0.00239	0.00096
W initial income	−0.62612	−0.61422	−0.60186	0.00516
W agricultural emp.	−0.00138	−0.00098	−0.00059	0.00016
W construction empl.	−0.11081	−0.10317	−0.09489	0.00340
W textiles empl.	0.00058	0.00089	0.00118	0.00012
W fuels xhemicals, trubber empl.	−0.00457	−0.00335	−0.00209	0.00053
W electronics empl.	−0.00372	−0.00295	−0.00214	0.00033
W trans. equip. empl.	0.00078	0.00153	0.00231	0.00031
W wholesale and retail trade empl.	0.04150	0.04516	0.04877	0.00160
W hotels, restaurants empl.	0.02882	0.03218	0.0357	0.00146
W trant. public utilities empl.	0.00301	0.00447	0.00604	0.00067
W finance empl.	−0.00880	−0.00764	−0.00654	0.00048
W other services empl.	0.05216	0.05759	0.06314	0.00232
W physical capital	−0.00865	−0.00681	−0.00495	0.00083
W patents	0.00050	0.00081	0.00109	0.00013
W human capital	−0.12741	−0.12135	−0.11517	0.00268
W high-technology patents	0.00044	0.00063	0.00081	0.00008
W population density	−0.02460	−0.02266	−0.02076	0.00085/
W area	0.00867	0.01046	0.01217	0.00074
W market potential	0.00116	0.00276	0.00437	0.00069
W specialization	−0.01627	−0.01036	−0.00432	0.00256
W diversity	0.00561	0.01428	−0.02312	0.00370
ρ	0.60480	0.61802	0.63126	0.00563

only those estimates that were significantly different from zero (based on the credible intervals).

Because the dependent variable in our model reflects logged levels of income, coefficient estimates associated with explanatory variables in log form such as the various industry employment variables, patents, human capital, area, fixed capital, etc. can be interpreted on an elasticity scale. This is, of course, subject to the caveat noted Section 2.3 regarding interpretation of spatial regression coefficients. The estimates in Table 3 cannot be interpreted in the usual regression model partial derivative sense, and in the next section we will provide direct and indirect impact estimates that describe how changes in the explanatory variables affect the level (and growth rates) of income. It is interesting to note that the coefficient on the spatial lag of initial income equals -0.61422, which our theoretical development from (11) suggests should equal $-\rho$, which is reported in the table to equal 0.61802, so we have agreement to two decimal places. Another point that can be gleaned from the estimates pertains to our argument regarding omitted variables. A test of the common factor restriction that $\beta_2 = -\rho\beta_1$ should fail in the presence of omitted variables. This is indeed the case, which can be illustrated using the coefficient on human capital. From the table, $-\rho\beta_1 = -0.075$, whereas $\beta_2 = -0.121$, with an average standard error equal to 0.0024, suggesting that β_2 is over 30 standard deviations away from $-\rho\beta_1$.

Since the table reports only model averaged estimates that are significantly different from zero, we see that there are 21 spatially lagged variables and only 13 explanatory variables that are different from zero. This points to the importance of neighbouring regions' characteristics in explaining variation in income levels. A comparison of the six coefficients associated with industry employment explanatory variables where spatial lags arise indicates that in four of the six cases the spatial lags have larger coefficients (agriculture, construction, textiles and hotels-restaurants). Since these variables and their spatial lags are on the same scale, this suggests that models ignoring the industry composition of neighbours may be excluding important influences. In addition, human capital and (logged) high-technology patents in 1995 represent cases where the own variable and spatial lag are roughly equal in size, again pointing to the importance of neighbouring region characteristics.

3.4. Coefficient Impact Estimates

As indicated in Section 2.3, we need to interpret the magnitude of the coefficient estimates from spatial regression models in light of the dependence structure. Past studies have incorrectly interpreted the signs on the spatially lagged variables as indicating the impact of neighbouring regions on the dependent variable (the growth rates). For example, the positive sign on neighbouring regions' initial income levels has been interpreted to mean that having neighbouring regions with higher levels of initial period income leads to higher growth rates. Similarly, the negative sign on the coefficient associated with neighbouring regions' human capital would be interpreted to mean that higher levels of educational attainment in neighbouring regions would exert a negative impact on income growth. As noted in Section 2.3, this is an incorrect interpretation of the coefficient estimates from a spatial regression model containing a spatial lag of the dependent variable.

Intuitively, in a model containing spatial lags of the dependent variable, the level of income (or growth rates) of each region i, which we denote y_i,depends on:

(1) levels from nearby regions captured by the spatial lag variable $W_i y$ (where W_i represents the ith row of the matrix W), (2) the own region initial level of income, (3) own region characteristics reflected by X_i, (4) the initial level of income in neighbouring regions represented by the spatial lag variable, and (5) characteristics of neighbouring regions captured by the spatial lag variables $W_i X$. In this type of model, a change in the initial level of income of region i will exert a *direct effect* on the income level (or growth rate) of region i, but also an *indirect impact*, because neighbouring regions' $j \neq i$ income (and growth rates) will be influenced by these changes. The altered initial income level will appear in the spatial lag for neighbouring regions, thereby impacting the income of neighbouring regions, which in turn impacts region i through the spatial lag variable $W_i y$. We need to keep in mind that each region is a neighbour to its neighbouring regions, so that feedback effects are intrinsic to spatial regression models.

It is also the case that changes in the initial level of income of region j will impact region j directly and therefore indirectly the income of neighbouring regions such as i. This is because any factor that influences income of region j in a model containing spatial lags Wy will also influence neighbouring regions' income.

To quantify these complex spatial interactions we rely on the set of scalar summary measures outlined in Section 2.3. A set of MCMC draws will be used to produce estimates of the total, direct and indirect impact estimates along with measures of dispersion and inferences regarding the significance of these impacts. Details regarding the specific calculations required are set out in Pace & LeSage (2008).

The scalar summary direct impact measures are reported in Table 4, with indirect and total impact estimates reported in Tables 5 and 6. These estimates are based on retained draws from model averaged estimates constructed using the 500 highest posterior probability models. As noted, these 500 models accounted for 99.77% of the posterior probability mass, and we use the symbol ⋆ to indicate impact estimates that are not significantly different from zero (at the 99% level). These measures reflect: (1) the direct impact, (2) the indirect impact, and (3) the total impact on regional income (and growth rates) that would arise from changing each variable in the model, *ceteris paribus*.

A comparison of the direct impact estimates and the model averaged estimates associated with the non-spatially lagged variables presented in the table for reference shows that in most cases these two sets of estimates are similar in magnitude. The difference between the estimates is due to feedback effects. For example, the difference between the direct impact estimate for an initial income of 0.7339 and the 0.7503 model averaged estimate represents the effect of changes in the initial income level influencing neighbouring regions' income levels, which feed back to influence own region income. In a few cases the feedback effects are large, resulting in a discrepancy between the direct impact coefficients and the model averaged estimates. For example, the model averaged estimates for construction, wholesale and retail trade and hotels and restaurant employment were 0.0141, 0.00018, and 0.00072, respectively, whereas the direct impact estimates were 0.0038, 0.0051, and 0.0043. The smaller impact estimate for construction employment indicates that feedback effects diminished the importance of changes in this variable on income levels, whereas the larger impact estimates for wholesale and retail trade and hotels and restaurant employment suggest that feedback effects increased the importance of these two industry composition variables. Intuitively, we might expect that changes in wholesale and retail trade

Table 4. Direct impact estimates

Variables	Lower 01 interval	Posterior mean	Upper 99 interval	Model averaged	Posterior SD
Initial income	0.7266	0.7339	0.7407	0.7503	0.0031
Agricultural empl	− 0.0009	− 0.0006	− 0.0002	− 0.0004	0.0001
Construction empl	0.0001	0.0038	0.0074	0.0141	0.0015
Food, beverage, tobacco empl.	− 0.0006	− 0.0001	0.0003	− 0.0001	0.0002*
Textiles empl	− 0.0003	-0.0002	-0.0001	− 0.0002	0.0001
Fuels, chemicals, rubber empl.	− 0.0005	− 0.0003	− 0.0001	0.0000	0.0001
Electronics empl	− 0.0012	− 0.0008	− 0.0003	− 0.0004	0.0002
Trans. equip, empl.	− 0.0006	-0.0003	0.0000	-0.0004’	0.0001*
Other manufacturing empl.	− 0.0002	− 0.0000	0.0002	− 0.0000	0.0001*
Wholesale and retail trade empl.	0.0040	0.0051	0.0062	0.0001	0.0005
Hotels, restaurants empl.	0.0038	0.0043	0.0048	0.0007	0.0002
Tran, public utilities empl.	0.0084	0.0105	0.0125	0.0093	0.0009
Finance emp	0.0549	0.0592	0.0636	0.0562	0.0019
Other services empl	0.0056	0.0065	0.0072	0.0001	0.0004
Physical capital	− 0.0008	− 0.0003	0.0002	0.0004	0.0002*
Patents	0.0003	0.0005	0.0006	0.0003	0.0001
Human capital	0.1130	0.1180	0.1233	0.1229	0.0022
High-technology patents	0.0003	0.0008	0.0012	0.0006	0.0002
Population density	− 0.2261	− 0.2181	− 0.2105	− 0.2019	0.0033
Area	− 0.2227	− 0.2156	− 0.2087	− 0.2030	0.0030
Market potential	− 0.0028	− 0.0002	0.0024	− 0.0004	0.0011*
Specialization	− 0.0020	− 0.0010	0.0000	0.0000	0.0004*
Diversity	− 0.0060	− 0.0034	− 0.0009	− 0.0046	0.0011

*Indicates not statistically different from zero.

and hotels and restaurant employment in one region would have large feedback effects on regional income levels. With the exception of these three cases, use of the model averaged estimates associated with the explanatory variables would provide a reasonable measure of the direct impact that arises from changes. However, we note that even in the case of the initial income level where the impact estimate was 0.7339 and the model averaged estimate was 0.7503, this small discrepancy was statistically meaningful, as indicated by the upper 0.01 bound on the impact estimate of 0.7407, suggesting a significant feedback effect.

Turning to the indirect impact estimates in Table 5, we note large discrepancies between these estimates and the model averaged coefficients on the spatially lagged explanatory variables. The estimates associated with the spatially lagged variables are often interpreted (incorrectly) as measures of the size and significance of indirect impacts in spatial regression models. As the discrepancies in the table indicate, this could lead to incorrect inferences about the true role of neighbouring regions' characteristics. For example the model averaged coefficient reported in Table 3 for the initial level of income is -0.6142, whereas the mean indirect impact estimate for this variable is a considerably smaller -0.3774.

Pace & LeSage (2008) point out that indirect impact estimates can be interpreted in two ways, one associated with averaging over the rows of the matrix S_r, and the other with averaging over the columns. One interpretation reflects how a change in the initial level of income of all regions by some constant amount would impact the income level of a typical region/observation. Pace & LeSage (2008) label this as the *average total impact on an observation*. The estimate of

Table 5. Indirect impact estimates

Variables	Lower 01 interval	Posterior mean	Upper 99 interval	Model averaged	Posterior
Initial income	− 0.4051	− 0.3774	− 0.3489	− 0.6142	0.0120
Agricultural empl.	− 0.0042	-0.0032	− 0.0021	− 0.0009	0.0005
Construction empl	− 0.2566	-0.2370	− 0.2174	− 0.1031	0.0085
Food, beverage, tobacco empl.	− 0.0012	0.0000	0.0013	0.0000	0.0005*
Textiles empl	0.0011	0.0018	0.0026	0.0008	0.0003
Fuels, chemicals, rubber empl.	− 0.0114	− 0.0083	− 0.0051	− 0.0033	0.0014
Electronics empl.	− 0.0101	− 0.0080	− 0.0058	− 0.0029	0.0009
Trans. equip. empl.	0.0014	0.0032	0.0051	0.0015	0.0008
Other manufacturing empl.	− 0.0010	0.0007	0.0024	0.0003	0.0008*
Wholesale and retail trade empl.	0.1035	0.1136	0.1231	0.0451	0.0044
Hotels, restaurants empl	0.0731	0.0819	0.0909	0.0321	0.0038
Tran. public utilities empl.	0.0209	0.0258	0.0308	0.0044	0.0022
Finance empl	0.0601	0.0680	0.0764	− 0.0076	0.0034
Other services empl	0.1304	0.1448	0.1590	0.0575	0.0062
Physical capital	− 0.0213	− 0.0164	− 0.0118	− 0.0068	0.0021
Patents	0.0018	0.0026	0.0034	0.0008	0.0003
Human capital	− 0.1259	− 0.1138	− 0.1019	− 0.1213	0.0053
High-technology patents	0.0018	0.0027	0.0035	0.0006	0.0003
Population density	− 0.3942	− 0.3702	− 0.3486	− 0.0226	0.0096
Area	− 0.3095	− 0.2887	− 0.2694	0.0104	0.0084
Market potential	0.0007	0.0062	0.0116	0.0027	0.0024
Specialization	− 0.0410	− 0.0259	− 0.0107	− 0.0103	0.0065
Diversity	0.0070	0.0286	0.0513	0.0142	0.0094

*Indicates not statistically different from zero.

the indirect impact is equal to -0.3774, so a 1% increase in the initial level of income of all other regions would decrease the income level of a typical region by 0.37%. This indirect impact takes into account the fact that the change in initial income negatively impacts other regions' income, which in turn negatively influences our typical region's income due to the presence of positive spatial dependence on neighbouring regions' income.

The second interpretation measures the cumulative impact of a change in region *i*'s initial level of income averaged over all other regions, which Pace & LeSage (2008) label the *average total impact from an observation*. Using this interpretation, the effect of changing a single region's initial level of income by 1% on each of the other regions' income is small, but cumulatively the impact measures -0.3774%. Of course, the effect on regions closely related to region i where the change in initial income took place will be greater than the effect on more remotely related regions. The magnitudes of the effects are the same from both interpretations, since the (average) row and column sums of S_r are the same.

To illustrate this, Figure 1 shows a graphical illustration of the profiles for both the cumulative and marginal indirect impacts arising from changes in the initial level of income of region i. The horizontal axis shows these two measures of indirect impact magnitudes associated with zero-order, first-order, second-order, and higher order neighbours. One way to view these profiles would be to associate an 8-year time span with each order or round on the horizontal axis. This is because the sample separation of $T=8$ years between the dependent and independent variables in our model was used. Therefore, each order of neighbours can be

Table 6. Total impact estimates

Variables	Lower 01 interval	Posterior mean	Upper 99 interval	Posterior SD
Initial income	0.3275	0.3565	0.3848	0.0122★
Agricultural empl	−0.0051	−0.0037	−0.0024	0.0006
Construction emp	−0.2538	−0.2332	-0.2131	0.0088
Food, beverage, tooacco empl.	−0.0017	−0.0001	0.0015	0.0007★
Textiles empl	0.0008	0.0016	0.0025	0.0004
Fuels, chemicals, rubber empl.	−0.0118	−0.0085	−0.0053	0.0014
Electronics empl	−0.0111	−0.0088	−0.0063	0.0010
Trans. equip, empl.	0.0010	0.0030	0.0049	0.0008
Other manufacturing empl.	−0.0012	0.0007	0.0025	0.0008★
Wholesale and retail trade empl.	0.1081	0.1187	0.1289	0.0047
Hotels, restaurants empl	0.0771	0.0862	0.0956	0.0040
Trans.public utilities empl.	0.0298	0.0363	0.0429	0.0028
Finance empl	0.1154	0.1272	0.1396	0.0050
Other services empl	0.1358	0.1512	0.1662	0.0065
Physical capital	−0.0219	−0.0167	−0.0117	0.0023
Patents	0.0021	0.0031	−0.0039	0.0004
Human capital	−0.0095	0.0042	0.0166	0.0057★
High-technology patents	0.0022	0.0035	0.0046	0.0005
Population density	−0.6168	−0.5883	−0.5620	0.0118
Area	−0.5292	−0.5044	−0.4807	0.0104
Market potential	−0.0016	0.0060	0.0133	0.0032★
Specialization	−0.0428	−0.0269	−0.0111	0.0068
Diversity	0.0028	0.0252	0.0492	0.0100

★Indicates not statistically different from zero.

viewed as a round that takes T years. Taking this view, spillover impacts gradually spread to higher order neighbours over time in a diffusion-type process, whose space–time profile is shown by the cumulative and marginal effects estimates in the figure.

The bottom panel of the figure shows the marginal impacts associated with each round of T years, which also represent the order of neighbours in these models. Given the estimated value $\overline{\rho} = 0.61$, we can calculate a half-life time that measures the amount of time required to reach the half-way point of the path to the new equilibrium steady state. Recall that changes in the explanatory variables lead to a series of space–time changes in this model that result in a new equilibrium, which should take $k = -\ln(2)/\ln(0.61) = 1.4$ rounds of 8 years, or 11.2 years to reach. This should not be confused with the conventional notion of half-life time to convergence which relates to the time required for the dependence on the initial state to wear off.

From the bottom panel of the figure, showing the marginal effects profile over time/space, we see that the period zero indirect effect of -0.15 associated with a change in the initial level of income gradually dies down, with the half-life point around 1.4 rounds or 11.2 years, where we reach -0.075, half of the period zero impact. We can also see from the cumulative effects profile that 1.4 rounds or 11.2 years moves us half way from the initial -0.15 to the final value of -0.3774, or around -0.26, associated with W order 1.4. The first round effect will fall on first-order neighbours, those identified by the matrix W. When we move to second-order neighbours associated with the matrix W^2 the marginal impact falls to around -0.06, and the cumulative impacts shown in the top panel indicate that by the

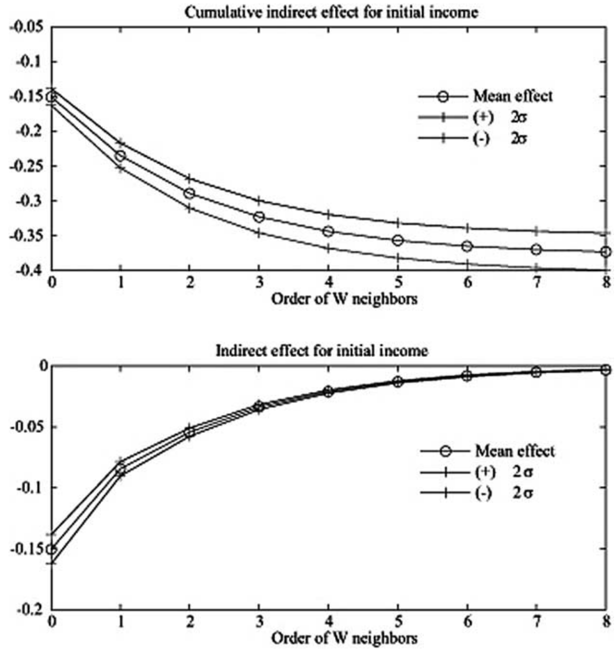

Figure 1. Cumulative and marginal indirect impact magnitudes of initial income levels.

eighth-order neighbours the indirect impact will have reached -0.36, reflecting most of its cumulative value of -0.3774.

A comparison of the indirect effects reported in Table 5 with the estimates for the spatial lags or the explanatory variables reported in Table 3 shows two cases where using the model averaged estimates from the spatial lags of the explanatory variables to infer the impact of changes in neighbouring regions' characteristics would lead to the wrong sign. There is a negative sign on the model averaged estimate for employment in the finance industry, whereas the indirect impact estimate is positive (and significant). Similarly, there is a positive sign on the model averaged estimate for the spatial lag of area, and a negative indirect impact estimate.

Another result of interest is that the impact estimates for the spillover effects arising from changes in 1995 patents and high-technology patents (knowledge transmission) are much larger than one would infer from the model averaged coefficient estimates on the spatial lag variables. Larger indirect impact estimates also arise for population density, market potential, specialization and diversity—all variables that have been of interest in the growth literature. The definition of diversity follows Glaeser *et al.* (1992), with lower numbers reflecting more diversity and higher proportions less diversity. Therefore, the positive indirect impact estimate for diversity indicates that higher levels of diversity (in neighbouring regions' patenting activities) negatively impact income levels. The same is true for specialization.

Considering the negative indirect impact of both human and physical capital using the second interpretation, we see that the (negative) cumulative spillover effect suggests that increases in region *i*'s human or physical capital will (on average over all other regions) lead to a decrease in income. For the first interpretation, we would infer that an increase in human or physical capital of all regions by some constant amount would lead to a negative impact on income of the typical region.

The total impact estimates reported in Table 6 measure the sum of the direct and indirect impacts from the previous two tables. From these estimates we see the somewhat surprising result that taking into account the positive direct impact of human capital along with the negative indirect impact leads to a total impact that is not significantly different from zero. In particular applications it may be more intuitive to think about the impact of changes in the explanatory variables by taking one or the other of the two interpretative views discussed above. Since the scalar summary magnitudes representing the average overall impacts are numerically equivalent, we are free to do this. Regarding the lack of impact arising from human capital, it seems more intuitive that raising initial levels of human capital for all regions would likely have no significant total impact on the income (or growth rates) of a typical region. This represents what Pace & LeSage (2008) label the *average total impact on an observation* from a change in human capital levels during the initial period. The intuition here arises from the notion that it is relative regional advantages in human capital that matter most for income (and growth), so changing human capital across all regions should have little or no total impact on (average) income (or growth rates). This interpretative view is consistent with our finding that the scalar summary measure for total impact of a change in human capital is not significantly different from zero.

We also see that the total impact of initial income levels is positive, suggesting that higher initial income levels lead to higher current levels of regional income. Patents and high-technology patents have the expected positive effect, whereas both specialization and diversity exert a negative impact (recall that diversity is defined inversely). Employment in the wholesale and retail trade, hotels and restaurants, textiles, transportation and public utilities, finance and other services has a positive impact on income levels, whereas agriculture, construction, fuels, chemical and rubber, and electronics employment is negative. Finally, population density and area both have large negative impacts.

4. Conclusion

We have attempted to clarify a number of points of confusion that have appeared in studies using spatial regression models for regional growth analysis. Like the case of non-spatial growth regressions, the effect of initial regional income levels wears off over time for spatial regression models, leaving us with a situation where regional characteristics are primary determinants of long-run regional income levels. However, in contrast to non-spatial growth regressions, long-run steady-state regional income depends on: (1) own-region as well as (2) neighbouring region characteristics, (3) the spatial connectivity structure of the regions, and (4) the strength of spatial dependence. Given this, the search for regional characteristics that exert important influences on income levels or growth rates should take place using spatial econometric methods that account for spatial dependence as well as own and neighbouring region characteristics, and the type of spatial regression model specification and weight matrix. The framework adopted here illustrated a unified approach for dealing with these issues.

Past non-spatial growth regression studies have placed a great deal of emphasis on uncertainty regarding model specification, specifically, the appropriate explanatory variables. However, the role of neighbouring region characteristics as well as spatial spillover effects has been ignored.

Consistent with our theoretical development, the empirical results reported here make it clear that the characteristics of neighbouring regions play an important role in determining regional income. Our findings indicate that indirect effects or spatial spillovers are perhaps more important than the direct effects of regional characteristics that have been the focus of non-spatial growth regressions. For example, when appropriately measuring the direct as well as indirect impact of changes in explanatory variables such as human capital on income levels we find that spatial spillovers may negate the direct positive impact on income levels (or equivalently income growth). While the direct (own region) impact on income of this variable is positive as we would expect, the spatial spillover impact on neighbouring regions is negative, producing an overall insignificant impact. This type of finding suggest a possible divergence between the interests of regional officials and those who take a broader perspective of society at large, say EU officials.

Another example of this type of divergence between regional and EU officials' incentives would be diversity. Regional officials would have an incentive to promote diversity since it has a small positive impact on income growth, whereas the spatial spillover impacts on neighbouring regions are negative and quite large. Similarly, specialization has an insignificant direct impact on regional income, but a large negative spatial spillover impact on neighbouring regions.

Notes

1. The authors would like to thank R. Kelley Pace for bringing this point to our attention.
2. See (13) and the related discussion.
3. Fernández *et al.* (2001a, b) provide details on calculations of probabilities for inclusion of individual variables in the models.
4. The two NUTS 2 regions of Brandenburg Nordost and Brandenburg Südwest were merged because of lack of data.
5. The two NUTS 2 regions of Provincia Autonoma Bolzano/Bazen and Provincia Autonoma Trento were merged because of lack of data.
6. These results are consistent with findings from Fernández et al. (2001a) for the case of leasts-squares mocleis, LeSage & Parent (2007) for spatial autoregressive models, and LeSage & Pace (2007) for matrix exponential spatial models.

References

Abreu, M., de Groot, H. L. F. & Florax, R. J. G. M. (2004) *Space and Growth: a Survey of Empirical Evidence and Methods*, Tinbergen Institute Working Paper No. TI 04-129/3. Internet site: http://ssrn.com/abstract = 631007

Anselin, L. & Le Gallo, J. (2006) Interpolation of air quality measures in hedonic house price models: spatial aspects, *Spatial Economic Analysis*, 1(1), 31–52.

Dall'erba, S. & Le Gallo, J. (2008) Regional convergence and the impact of European Structural Funds over 1989–1999: a spatial econometric analysis, *Papers in Regional Science*, 87(2), 219–244.

Debreu, G. & Herstein, I. N. (1953) Nomiegative square matrices, *Econometrica*, 21, 597–607.

Denison, D. G. T, Mallick, B. K. & Smith, A. F. M. (1998) Automatic Bayesian curve fitting, *Journal of the Royal Statistical Society, Series B*, 60(2), 333–350.

Durlauf, S. N. (2001) Manifesto for a growth econometrics, *Journal of Econometrics*, 100, 65–69.

Fernández, C, Ley, E. & Steel, M. F. J. (2001a) Model uncertainty in cross-country growth regressions, *Journal of Applied Econometrics*, 16(5), 563–576.

Fernández, C, Ley, E. & Steel, M. F. J. (2001b) Benchmark priors for Bayesian model averaging, *Journal of Econometrics*, 100(2), 381–127.

Fingleton, B. (2001) Theoretical economic geography and spatial econometrics: dynamic perspectives, *Journal of Economic Geography*, 1, 201–225.

Fischer, M. M. & Stirböck, C. (2006) Pan-European regional income growth and club-convergence, *Annals of Regional Science*, 40(4), 693–721.

Glaeser, E. L., Kallal, H. D, Scheinkman, J. A. & Shleifer, A. (1992) Growth in cities, *Journal of Political Economy*, 100(61), 1127–1152.

Harris, C. (1954) The market as a factor in the localization of industry in the United States, *Annals of the Association of American Geographers*, 64, 315–348.

Kelejian, H. H., Tavlas, G. S. & Hondronyiannis, G. (2006) A spatial modeling approach to contagion among emerging economies, *Open Economies Review*, 17(4/5), 423–442.

Koop, G. (2003) *Bayesian Econometrics*, Chichester, John Wiley.

LeSage, J. P. & Pace, R. K. (2007) A matrix exponential spatial specification, *Journal of Econometrics*, 140(1), 190–214.

LeSage, J. P. & Pace, R. K. (2008) Spatial econometric modeling for origin–destination flows, *Journal of Regional Science* (forthcoming).

LeSage, J. P. & Pace, R. K. (2008) *Introduction to spatial econometrics*, Taylor & Francis CRC Press, Boca Raton (forthcoming).

LeSage, J. P. & Parent, O. (2007) Bayesian model averaging for spatial econometric models, *Geographical Analysis*, 39(3), 241–267.

López-Bazo, E., Vayá, E. & Artis, M. (2004) Regional externalities and growth: evidence from European regions, *Journal of Regional Science*, 44(1), 43–73.

Madigan, D. & York, J. (1995) Bayesian graphical models for discrete data, *International Statistical Review*, 63(2), 215–232.

Raftery, A. E., Madigan, D. & Hoeting, J. A. (1997) Bayesian model averaging for linear regression models, *Journal of the American Statistical Association*, 92(437), 179–191.

Sala-i-Martin, X., Doppelhofer, G. & Miller, R. I. (2004) Determinants of long-term growth: a Bayesian Averaging of Classical Estimates (BACE) approach, *American Economic Review*, 94(4), 813–835.

Verspagen B. , Van Moergastel, T. & Slabbers, M. (1994) MERIT Concordance Table: IPC-ISIC (rev. 2), Maastricht, Maastricht Economic Research Institute on Innovation and Technology, University of Limburg.

Zellner, A. (1971) *An Introduction to Bayesian Inference in Econometrics*, New York, John Wiley.

Appendix A

This study disaggregates Europe's territory into 255 NUTS 2 regions. These cover the whole of Europe except South East Europe, Cyprus, Malta, Iceland and Liechtenstein, rather than just taking the EU 15 as in many studies. NUTS is an acronym of the French for 'the nomenclature of territorial units for statistics', which is a hierarchical system of regions used by the statisticai office of the European Community for the production of regional statistics. At the top of the hierarchy are NUTS 0 regions (countries), below which are NUTS 1 regions and then NUTS 2 regions. Although varying considerably in size, the NUTS 2 region is widely viewed as the most appropriate unit for modelling and analysis purposes (see, for example, Fingleton, 2001). The sample is composed of 255 NUTS 2 regions located in the 25 EU member states (except Cyprus and Malta) plus Norway and Switzerland. We exclude the Spanish North African territories of Ceuta y Melilla, the Portuguese non-Continental territories of the Azores and Madeira, and the French Départements of d'Outre-Mer Guadeloupe, Martinique, French Guayana and Réunion. Thus, we include the following NUTS 2 regions:

Austria: Burgenland; Niederösterreich; Wien; Kärnten; Steiermark; Oberösterreich; Sgzburg; Tirol; Vorarlberg.

Belgium: Région de Bruxelles-Capitale/Brussels Hoofdstedelijk Gewest; Prov. Antwerppen; Prov. Limburg (BE); Prov. Oost-Vlaanderen; Prov. Vlaams-Brabant; Prov. WestVlaanderen; Prov. Brabant Wallon; Prov. Hainaut; Prov. Liège; Prov. Luxembourg (BE); Prov. Namur.

Czech Republic: Praha; Stední echy; Jihozápad; Severozápad; Severovýchod; Jihovýchod; Stedmní Morava; Moravskoslezsko.
Denmark: Danmark.
Germany: Stuttgart; Karlsruhe; Freiburg; Tübingen; Oberbayern; Niederbayern; Oberpfalz; Oberfranken; Mittelfranken; Unterfranken; Schwaben; Berlin; Brandenburg Nordost & Brandenburg Südwest;[4] Bremen; Hamburg; Darmstadt; Gießen; Kassel; Mecklenburg Vorpommern; Braunschweig; Hannover; Lüneburg; Weser-Ems; Diisseldorf; Köln; Münster; Detmold; Arnsberg; Koblenz; Trier; Rheinhessen-Pfalz; Saarland; Chemnitz; Dresden; Leipzig; Dessau; Halle; Magdeburg; Schleswig-Holstein; Thüringen.
Estonia: Eesti.
Greece: Anatoliki Makedonia, Thraki; Kentriki Makedonia; Dytiki Makedonia; Thessalia; Ipeiros; Ionia Nisia; Dytiki Ellada; Sterea Ellada; Peloponnisos; Attiki; Voreio Aigaio; Notio Aigaio; Kriti.
Spain: Galicia; Principado de Asturias; Cantabria; País Vasco; Comunidad Foral de Navarra; La Rioja; Aragón; Comunidad de Madrid; Castilla y León; Castilla-La Mancha; Extremadura; Cataluña; Comunidad Valenciana; Illes Balears; Andalucía; Región de Murcia.
France: Île-de-France; Champagne-Ardenne; Picardie; Haute-Normandie; Centre; Basse-Normandie; Bourgogne; Nord-Pas-de-Calais; Lorraine; Alsace; Franche-Comté; Pays de la Loire; Bretagne; Poitou-Charentes; Aquitaine; Midi-Pyrénées; Limousin; Rhône-Alpes; Auvergne; Languedoc-Roussillon; Provenee-Alpes-Côte d'Azur; Corse.
Ireland: Border, Midland and Western; Southern and Eastern.
Italy: Provincia Autonoma Bolzano/Bozen & Provincia Autonoma Trenta[5]; Piemonte; Valle d'Aosta/Vallée d'Aoste; Liguria; Lombardia; Veneto; Friuli-Venezia Giulia; Emilia-I Romagna; Toscana; Umbria; Marche; Lazio; Abruzzo; Molise; Campania; Puglia; Basilicata; Calabria; Sicilia; Sardegna.
Latvia: Latvija.
Lithuania: Lietuva.
Luxembourg: Luxembourg (Grand-Duché).
Hungary: Közép-Magyarország; Közép-Dunántúl; Nyugat-Dunántúl; Dél-Dunántúl; Észak-Magyarország; Észak-Alföld; Dél-Alföld.
Netherlands: Groningen; Friesland; Drenthe; Overijssel; Gelderland; Flevoland; Utrecht; Noord-Holland; Zuid-Holland; Zeeland; Noord-Brabant; Limburg (NL).
Norway: Oslo og Akershus; Hedmark og Oppland; Sør-Østlandet; Agder og Rogaland; Vestlandet; TrøndeIag; Nord-Norge.
Poland: ódzkie; Mazowieckie; Maopolskie; lskie; Lubelskie; Podkarpackie; witokrzyskie; Podlaskie; Wielkopolskie; Zachodniopomorskie; Lubuskie; Dolnolslde; Opolskie; Kujawsko-Pomorskie; Warmisko-Mazurskie; Pomorskie.
Portugal: Norte; Algarve; Centra (PT); Lisboa; Alentejo.
Switzerland: Région lérnanique; Espace Mittelland; Nordwestschweiz; Zurich; Ostschweiz; Zentralschweiz; Ticino.
Slovenia: Slovenija.
Slovakia: Bratislavský kraj; Západné Slovensko; Stredné Slovensko; Vychodné Slovensko.
Finland: Itä-Suomi; Etelä-Suomi; Länsi-Suomi; Pohjois-Suomi; Åland.
Sweden: Stockholm; Östra Mellansverige; Sydsverige; Norra Mellansverige; Mellersta Norrland; Övre Norrland; Småland raed öarna; Västsverige.

United Kingdom: Tees Valley and Durham; Northumberland and Tyne and Wear; Cumbria; Cheshire; Greater Manchester; Lancashire; Merseyside; East Riding and North Lincolnshire; North Yorkshire; South Yorkshire; West Yorkshire; Derbyshire and Nottinghamshire; Leicestershire, Rutland and Northamptonshire; Lincolnshire; Herefordshire, Worcestershire and Warwickshire; Shropshire and Staffordshire; West Midlands; East Anglia; Bedfordshire and Hertfordshire; Essex; Inner London; Outer London; Berkshire, Buckinghamshire and Oxfordshire; Surrey, East and West Sussex; Hampshire and Isle of Wight; Kent; Gloucestershire, Wiltshire and North Somerset; Dorset and Somerset; Cornwall and Isles of Scilly; Devon; West Wales and the Valleys; East Wales; North Eastern Scotland; Eastern Scotland; South Western Scotland; Highlands and Islands; Northern Ireland.

Appendix B

The MC^3proced ure was run to produce 500,000 draws, allowing the variable selection procedure to select variables from the candidate variables in the explanatory variables matrix X as well as those in the spatial lagged explanatory variables matrix WX.

Running the MC^3 sampler for 500,000 draws produced over 200,000 unique models. Since we have 23 candidate variables in matrix X and another 23 in WX, there are $2^{46} = 7.0369e + 013$ possible models based on alternative ways to combine the 46 possible explanatory variables. Note that since we have three alternative distance measures for the weight matrix specification and vary the number of nearest neighbours from 1 to 10, there are another $3 \times 10 = 30$ possible spatial weight matrices that could be used with the set of explanatory variables to form a different model. As a test for convergence of the MC^3 procedure, we implemented another run involving 500,000 draws based on a different random sample of explanatory variables, weight matrix and number of nearest neighbours. This resulted in nearly identical results, suggesting that the MC^3 procedure is finding regions of the large model space that contain high posterior support while ignoring those regions with low support.

Despite the large number of models considered, the top 500 highest posterior probability models accounted for 99.77% of the posterior probability mass, with the top 200 models accounting for 92.5%, and the top 100 models 78%. This suggests a relatively small part of the large model space contains most of the posterior probability support[6] Only the 17 top models exhibited posterior probability support greater than 1% with the remaining models having posterior model probability support less than 1%.

It is interesting to note that only models based on spatial weight matrices constructed from the lorry drive time-based nearest neighbours appeared in the top 1,000 models, suggesting strong evidence in favour of this type of weight matrix. Intuitively, use of great circle distances in the context of European NUTS 2 regions will result in nearest neighbours that span seas and other physical obstacles that act as barriers to true spatial connectivity.

In contrast, the drive time distances (calculated on the basis of the IRPUD European road network database) evidently add some realism to the connectivity structure in the system of regions by taking into account different road types, national lorry speed limits, speed constraints in urban and mountainous areas as well as waiting times at borders and statutory rest periods for drivers.

The distribution of the number of nearest neighbours was also relatively concentrated for the case of the top 500 models, with five neighbours appearing in 350 of the 500 models, and eight neighbours appearing in 140 of these 500 models. For the case of the top 10 models we have six models with five neighbours, and 1 four with eight neighbours.