Regions, technological interdependence and growth in Europe

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Abstract.

This paper presents a theoretical neoclassical growth model with two kinds of capital, and technological interdependence among regions. Technological interdependence is assumed to operate through disembodied knowledge diffusion between technologically similar regions. The transition from theory to econometrics yields a reduced-form empirical model that in spatial econometrics literature is known as spatial Durbin model. Technological dependence between regions is formulated by a connectivity matrix that measures closeness of regions in a technological space spanned by 120 distinct technological fields. We use a system of 158 regions across 14 European countries over the period from 1995 to 2004 to empirically test the model. The paper illustrates the importance of an impact-based model interpretation, in terms of the LeSage and Pace (2009) approach, to correctly quantify the magnitude of spillover effects, in order to avoid incorrect inferences about the presence or absence of significant capital externalities and the role technological interdependence plays in regional growth processes in Europe.

Keywords: Economic growth, augmented Mankiw-Romer-Weil model, disembodied knowledge diffusion, technological similarity between regions, spatial econometrics

JEL Classification: C31, O18, O47, R11

1 Introduction

Neoclassical growth models postulate that physical capital accumulation contributes to the growth in the short-run, but long-run growth is totally determined by technological progress which is exogenous to the model so that there is no explicit role for knowledge spillovers (see Stiroh 2003). In this paper we account for disembodied knowledge diffusion in economic growth in the context of a neoclassical growth model that incorporates the essential elements of the Mankiw-Romer-Weil (MRW) model.

This paper assumes that all technological knowledge is embedded in physical and human capital[1], and builds on previous research of the author (see Fischer 2009). This previous work provides an open-economy extension of the Mankiw-Romer-Weil (MRW) model by accounting for technological interdependence among regional economies. Technological interdependence is assumed to operate through disembodied technology diffusion. Disembodied technology diffusion is the process whereby knowledge spreads through channels other than embedded in machinery. It originates in the externalities that characterize

[1] In order to avoid scale effects, we follow Jones (1995) by assuming that knowledge is embedded in the physical capital-labour and human capital-labour ratios and not in the levels.

the R&D process and the knowledge spillovers that occur when a firm develops a new idea or process and cannot fully appreciate the results of its R&D.

We know very little about how knowledge diffuses. While previous research[2] focuses on the spatial dimension, this paper shifts attention to the technological dimension to the spillover mechanism. According to this view the ability to make productive use of another's region knowledge depends on the degree of technological similarity between regions. Technological similarity is measured as closeness in technological space spanned by a number of technological fields. Every technological field has a somewhat unique set of applications, and researchers in similar technological fields interact in professional organizations, and publish in commonly read journals.

The paper is structured a follows. Section 2 presents the neoclassical growth model that accounts for technological interdependence among technologically similar regions. The reduced-form of the theoretical model leads to an associated reduced-form empirical model that in the spatial econometrics literature is known as spatial Durbin model specification. Section 3 briefly describes this model along with the relevant estimation approach. The inherent complexity of the spatial Durbin model specification means that treating the parameter estimates like least-squares parameter estimates is incorrect, as repeatedly noted by LeSage and Pace (2009). A change in any given explanatory variable in a regional economy affects the economy itself (direct impact) and other economies indirectly (indirect or spillover impact). These interrelations increase the difficulty of correctly interpreting the resulting estimates. Section 4 describes LeSage and Pace's (2009) computational approaches to calculating scalar summary measures of these impacts. In Section 5, we describe the data and the construction of the connectivity matrix that represents the technological closeness between the regions in the sample. Section 6 reports the estimation results using a sample of 158 NUTS-2 regions across 14 European countries, and illustrates the importance of the estimated impacts to avoid incorrect inferences about the true nature of regional growth processes in general and the correct degree of interdependence among technologically similar regions in particular. Section 7 concludes the paper.

2 Modelling regional growth

Consider a world consisting of *N* separate regional economies. These economies are similar in that they have the same production possibilities. They differ because of different endowments and allocations. The economies evolve independently in all respects except technological interdependence.

In each regional economy *i*, individuals can produce a consumption-capital good that we will term output. Total output, Y_{it}, produced at time *t* is given by a Cobb-Douglas production function

$$Y_{it} = A_{it}\ K_{it}^{\alpha_K}\ H_{it}^{\alpha_H}\ L_{it}^{1-\alpha_K-\alpha_H} \qquad (1)$$

where K_{it} is physical capital, H_{it} human capital, L_{it} labour employed to produce output, and A_{it} the level of technological knowledge available to this region. α_K and α_H are the output elasticities with respect to physical and human capital. Note that there are constant returns to scale in *K*, *H* and *L*. As in Mankiw, Romer and Weil (1992) we assume $\alpha_K + \alpha_H < 1$, and $\alpha_K, \alpha_H > 0$ which implies that there are decreasing returns to both types of capital.

[2] See López-Bazo, Váya and Artís (2004), Ertur and Koch (2007) and Fischer (2009).

We now discuss each element of this production function in turn. First, physical and human capital are accumulated as described by

$$\dot{K}_{it} = s_i^K \; Y_{it} - \delta K_{it} \tag{2}$$

$$\dot{H}_{it} = s_i^H \; Y_{it} - \delta H_{it} \tag{3}$$

where the dots over *K* and *H* represent the derivatives with respect to time. The variables s_i^K and s_i^H denote the constant, but distinct investment rates for physical and human capital, respectively, and $\delta > 0$ is the exogenous, constant rate of depreciation identical for all capital.

Next, aggregate labour employed producing output grows exogenously at the fixed rate $n_i > 0$.

$$\dot{L}_{it} = n_i \; L_{it}. \tag{4}$$

The final factor in the production of output is the aggregate level of technological knowledge A_{it}, available in region *i* at time *t*. We assume that

$$A_{it} = \Omega_t \; k_{it}^{\theta} \; h_{it}^{\phi} \prod_{j \neq i}^{N} A_{jt}^{\rho T_{ij}} \tag{5}$$

which views A_{it} to depend on four terms. The first term, Ω_t, is used – as in Mankiw, Romer and Weil (1992) – to represent that amount of knowledge created anywhere in the world of regions which is immediately available to be used in any economy. This part of region's *i* knowledge stock is exogenous and identical in all regions: $\Omega_t = \Omega_0 \exp(\mu t)$, where μ is its constant rate of growth.

Second, we assume that each region's aggregate level of knowledge increases with the aggregate level of physical capital per worker, $k_{it} = K_{it} / L_{it}$, and with the aggregate level of human capital per worker, $h_{it} = H_{it} / L_{it}$. The associated parameters θ with $0 \le \theta < 1$ and ϕ with $0 \le \phi < 1$ reflect spatial connectivity of k_{it} and h_{it} within region *i*, respectively[3].

Finally, we assume non-embodied knowledge diffusion to cause technological progress of region *i* to depend positively on the technological progress of other regions $j \neq i,$ for $j = 1, ..., N.$ The last term on the right hand side of Eq. (5) represents this technological dependence of region *i* from technologically neighbouring regions *j* which is formalized by means of connectivity terms T_{ij} that measure the closeness of regions *i* and *j* in a technological space spanned by a number of, say *F*, distinct technological fields. These terms are assumed to be non-negative, non-stochastic and finite, with the properties $0 \le T_{ij} \le 1,$ $T_{ij} = 0$ if $i = j,$ and $\sum_{j \neq i} T_{ij} = 1$ for $i = 1, ..., N,$ and may be organized to form a technological connectivity matrix ***T***, called technological weight matrix. The parameter ρ with $0 \le \rho < 1$ reflects the degree of technological interdependence in the system of regions. Note that regions neighbouring region *i* are defined as those regions *j* for which $T_{ij} > 0$. The more technologically similar a region *i* is

[3] We assume that each unit of capital investment increases not only the stock of capital, but also generates externalities which lead to knowledge spillovers that increase the level of technology for all firms in the region.

with region j, the higher T_{ij} is, and the more region i benefits from knowledge spilling over from region j.

Resolving Eq. (5) for A_{it} and replacing the result in the production function (1) written per worker, we get

$$y_{it} = \Omega_t^{\frac{1}{1-\rho}} \, k_{it}^{u_{ii}} \, h_{it}^{v_{ii}} \prod_{j \neq i}^{N} k_{jt}^{u_{ij}} \, h_{jt}^{v_{ij}} \tag{6}$$

with

$$u_{ii} = \alpha_K + \theta \left(1 + \sum_{r=1}^{\infty} \rho^r \, (\boldsymbol{T}^r)_{ii} \right) \tag{7}$$

$$u_{ij} = \theta \sum_{r=1}^{\infty} \rho^r \, (\boldsymbol{T}^r)_{ij} \quad \text{for } i \neq j \tag{8}$$

$$v_{ii} = \alpha_H + \phi \left(1 + \sum_{r=1}^{\infty} \rho^r \, (\boldsymbol{T}^r)_{ii} \right) \tag{9}$$

$$v_{ij} = \phi \sum_{r=1}^{\infty} \rho^r \, (\boldsymbol{T}^r)_{ij} \quad \text{for } i \neq j. \tag{10}$$

where $y_{it} = Y_{it} / L_{it}$, and $(\boldsymbol{T}^r)_{ij}$ is the (i, j)th element of the N-by-N connectivity matrix $\boldsymbol{T}$ taken to the power r, with the matrix $\boldsymbol{T}$ measuring the technological similarity between the N regions.

Then we can derive[4] the output per worker of region i at steady state as

$$\begin{aligned} \ln y_{it}^* = {} & \frac{1}{1-\eta} \ln \Omega_t + \frac{\alpha_K + \theta}{1-\eta} \ln s_i^K + \frac{\alpha_H + \phi}{1-\eta} \ln s_i^H - \frac{\eta}{1-\eta} \ln (n_i + g + \delta) \\ & - \frac{\alpha_K}{1-\eta} \rho \sum_{j \neq i}^{N} T_{ij} \ln s_j^K - \frac{\alpha_H}{1-\eta} \rho \sum_{j \neq i}^{N} T_{ij} \ln s_j^H + \\ & + \frac{\alpha_K + \alpha_H}{1-\eta} \rho \sum_{j \neq i}^{N} T_{ij} \ln (n_j + g + \delta) + \frac{1 - \alpha_K - \alpha_H}{1-\eta} \rho \sum_{j \neq i}^{N} T_{ij} \ln y_{jt}^* \end{aligned} \tag{11}$$

with $\eta = \alpha_K + \alpha_H + \theta + \phi$ and the balanced growth[5] rate $g = \mu [(1-\rho)(1 - \alpha_K + \ \ + \alpha_H) - \theta - \phi]^{-1}$. If $\theta = \phi = \rho = 0$ the model collapses to the conventional MRW model. It is important to note that Eq. (11) is valid only if the regions are at their steady states or if deviations from steady state are random.

This neoclassical growth model has the same qualitative predictions as the MRW model. The per worker output of region i at steady state depends positively on its own physical capital and human capital investment rates $(\ln s_i^K \text{ and } \ln s_i^H)$ and negatively on its population

[4] See Fischer (2009) for the proof.

[5] A balanced growth path is defined as a situation in which (i) per worker physical and human capital grow at the same rate denoted by g, (ii) the exogenous part of technology grows at the constant rate μ, and (iii) the population growth rate and the investment rates for physical and human capital are constant.

growth rate $\ln(n_i + g + \delta)$. Per worker output of region *i*, however, depends also on determinants that lie outside MRW's original theory. Per worker output of a region *i* at steady state is negatively influenced by investment rates for physical and human capital in technologically neighbouring regions j, for $j \neq i$, those identified by $T_{ij} > 0$, and positively influenced by their population growth rates. Even if the sign of the coefficients of the investment rates of neighbouring regions is negative, each of these investment rates ($\ln s_j^K$ and $\ln s_j^H$) positively influences the output per worker in the neighbouring regions at steady state ($\ln y_{jt}^*$), which in turn positively affects the per worker output of region *i* at steady state through the technological interdependence among the regions (see the last term on the right hand side of Eq. (11)). We note that if $\theta = \phi = \rho = 0$, Eq. (11) reduces to the conventional MRW steady state equation.

3 Model specification and estimation

It is easy to see that the empirical counterpart of the reduced form of the theoretical model given by Eq. (11) can be expressed at a given time (*t*=0 for simplicity) for region *i* as follows

$$\ln y_i = \beta_0 + \beta_1 \ln s_i^K + \beta_2 \ln s_i^H + \beta_3 \ln(n_i + g + \delta) + \gamma_1 \sum_{j \neq i}^{N} T_{ij} \ln s_j^K + \gamma_2 \sum_{j \neq i}^{N} T_{ij} \ln s_j^H + \gamma_3 \sum_{j \neq i}^{N} T_{ij} \ln(n_j + g + \delta) + \lambda \sum_{j \neq i}^{N} T_{ij}\, y_j + \varepsilon_i \qquad (12)$$

where $(1-\eta)^{-1} \ln \Omega_0 = \beta_0 + \varepsilon_i$ for $i = 1, ..., N$, with β_0 a constant and ε_i a region-specific shift or shock term[6]. Note that we have the following theoretical constraints between coefficients: $\beta_1 + \beta_2 + \beta_3 = 0$ and $\gamma_1 + \gamma_2 + \gamma_3 = 0$.

Rewriting Eq. (12) in matrix form gives

$$\boldsymbol{y} = \boldsymbol{\iota}_N \beta_0 + \boldsymbol{X\beta} + \boldsymbol{T\,X\,\gamma} + \lambda \boldsymbol{T\,y} + \boldsymbol{\varepsilon} \qquad (13)$$

with

y *N*-by-1 vector of observations on the per worker output level for each of the *N* regions,

X *N*-by-*Q* matrix of observations on the *Q* non-constant exogenous variables [here *Q*=3], including the vectors of the physical and human capital investment rates and the population growth rate for each of the *N* regions,

$\boldsymbol{\beta}$ *Q*-by-1 vector of the regression parameters associated with the *Q* non-constant exogenous variables [here: $\boldsymbol{\beta} = (\beta_1, \beta_2, \beta_3)'$],

TX *N*-by-*Q* matrix of the *Q* technologically lagged non-constant exogenous variables,

$\boldsymbol{\gamma}$ *Q*-by-1 vector of the regression parameters associated with the *Q* lagged non-constant exogenous variables [here: $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, \gamma_3)'$],

T y *N*-by-1 vector of the dependent technologically lagged variable that represents the technological interdependence between the regions,

[6] The term Ω_0 reflects – as Mankiw, Romer and Weil (1992) emphasize – not just technology, but also resource endowments, institutions and so on, and hence may vary across the regions.

λ the autoregressive parameter with $\lambda = (1-\alpha_K - \alpha_H)\rho / (\eta - 1)$,

$\boldsymbol{\iota}_N$ N-by-1 vector of ones with the associated scalar parameter β_0,

$\boldsymbol{\varepsilon}$ N-by-1 vector of errors assumed to be identically and normally distributed with zero mean: $\boldsymbol{\varepsilon} \sim N\ (\mathbf{0}, \sigma^2 \boldsymbol{I})$.

Note that all variables are in log form. The variables spanned by $\boldsymbol{X}$ represent the determinants that are suggested by the MRW model whereas $\boldsymbol{TX}$ represent those that lie outside MRW's original theory, as does $\boldsymbol{Ty}$ that represents the technological interdependence between the regions and defines the difference to a MRW world of closed regions.

In the spatial econometrics literature, a model specification like Eq. (13) is referred to as a spatial Durbin model. Maximizing the full log likelihood for this model would involve setting the first derivatives with respect to the parameters $\boldsymbol{\beta}, \boldsymbol{\gamma}, \sigma^2$ and λ equal to zero and simultaneously solving these first-order conditions for all the parameters. Equivalent ML estimates can be found using the log likelihood function concentrated with respect to the parameters $\boldsymbol{\beta}, \boldsymbol{\gamma},$ and σ^2 which takes the form

$$\ln \mathcal{L}(\lambda) = \frac{N}{2} \ln 2\pi + \ln |\boldsymbol{I} - \lambda \boldsymbol{T}| - \frac{1}{2} \ln (\hat{\boldsymbol{e}}_0 - \lambda \hat{\boldsymbol{e}}_L)' (\hat{\boldsymbol{e}}_0 - \lambda \hat{\boldsymbol{e}}_L). \qquad (14)$$

The notation $\ln \mathcal{L}(\lambda)$ in this equation indicates that the scalar concentrated log likelihood function value depends on the parameter λ. $\hat{\boldsymbol{e}}_0$ and $\hat{\boldsymbol{e}}_L$ are the estimated residuals in a regression of $\boldsymbol{y}$ on $\boldsymbol{U}$ and $\boldsymbol{Ty}$ on $\boldsymbol{U}$, respectively, with $\boldsymbol{U} = [\boldsymbol{\iota}_N\ \boldsymbol{X}\ \boldsymbol{TX}]$.

Optimizing $\ln \mathcal{L}(\lambda)$ with respect to λ permits us to find the ML estimate $\hat{\lambda}$ and to use this estimate in the closed form expressions for $\hat{\beta}(\hat{\lambda})$, $\hat{\gamma}(\hat{\lambda})$ and $\hat{\sigma}^2(\hat{\lambda})$ to produce ML estimates for these parameters. A variety of univariate optimization techniques may be used for optimizing the concentrated log likelihood function. In this study we use the simplex optimization technique.

4 Interpretation of estimated parameters

The reduced form of the theoretical model in Eq. (11) and the associated empirical model in Eq. (12) or Eq. (13) provide very rich own- and cross-partial derivatives that quantify the magnitude of direct and indirect (or spatial spillover) effects. A change in a single observation (region) associated with any MRW determinant will affect the region itself (a direct impact) and potentially affect all other regions indirectly (an indirect impact).

The non-independent relationship between changes in region *j*'s physical and human capital investment or population growth rates and region *i* implies that conventional regression interpretations of the parameter estimates are wrong, as noted by LeSage and Fischer (2008). We use the 2*Q* summary measures suggested by LeSage and Pace (2009) to measure the direct and indirect impacts for each of the three MRW variables. The direct impact is summarized using the average impact of a change in the given MRW variable at each of *N* locations on the dependent variable at the same location. The indirect impact that reflects spatial spillovers between technologically close regions is summarized by the average impact of a change in the MRW variable at each location on the dependent variable at different locations.

Formally, these summary impact measures of impact are defined as follows (see LeSage and Pace 2009, pp. 36-37):

(i) *The average direct impact*. The impact of changes in the *i*th observation of X_q (the *q*th column of $\boldsymbol{X}$, q=1, …, Q=3), which we denote by X_{iq}, on $\ln y_i$ can be summarized by measuring the average $\boldsymbol{S}_q(\boldsymbol{T})_{ii}$, which equals $N^{-1}tr(\boldsymbol{S}_q(\boldsymbol{T}))$ where $\boldsymbol{S}_q(\boldsymbol{T})_{ii}$ is the (i, i)th element of the N-by-N matrix

$$\boldsymbol{S}_q(\boldsymbol{T}) = (\boldsymbol{I} - \lambda \boldsymbol{T})^{-1}(\boldsymbol{I}\beta_q + \boldsymbol{T}\gamma_q) \qquad (15)$$

for $q = 1, ..., Q$. The diagonal elements of $\boldsymbol{S}_q(\boldsymbol{T})$ contain the direct impacts so that the average direct effect is constructed as an average of the diagonal elements.

(ii) *The average indirect impact*. The indirect effects that arise from changes in all observations $j = 1, ..., N$ of an explanatory variable are found as the sum of the off-diagonal elements of row *i* from the matrix $\boldsymbol{S}_q(\boldsymbol{T})$ given by Eq. (15). The average indirect impact is constructed as an average of the off-diagonal elements, where the off-diagonal row elements are summed up first, and then an average of these sums is taken.

Computing these direct and indirect summary impacts requires little additional computational cost. The low cost of computation allows simulating the distribution of the impacts to derive inference statistics based on the maximum likelihood parameter estimates.

5 Data and the technological weight matrix

The database that will be employed to estimate the model is composed of 158 NUTS-2 regions[7], over the period 1995-2004. The regions cover 14 European countries including Austria (nine regions), Belgium (11 regions), Denmark (one region), Finland (four regions), France (21 regions), Germany (40 regions), Italy (18 regions), Luxembourg (one region), the Netherlands (12 regions), Norway (seven regions), Portugal (four regions), Spain (15 regions), Sweden (eight regions) and Switzerland (seven regions).

We use gross value added, *gva*, as a proxy for regional output. *gva* is the net result of output at basic prices less intermediate consumption valued at purchasers' prices, and measured in accordance with the European System of Accounts 1995. The dependent variable is *gva* divided by the number of workers in 2004. We measure *n* as the growth rate of the working age population, where working age is defined as 15-64 years, and use gross fixed capital formation per worker as a proxy for physical capital investment. Following Mankiw, Romer and Weil (1992), we restrict our focus on investment in human capital in the form of education and take a proxy for the rate of human capital accumulation that measures the percentage of the working age population (15 years and older) with higher education as defined by the International Standard Classification of Education (ISCED) 1997 classes five

[7] We exclude the Spanish North African territories of Ceuta y Melilla, the Spanish Balearic islands, the Portuguese non-continental territories Azores and Madeira, the French Départements d'Outre-Mer Guadaloupe, Martinique, French Guayana and Réunion, and, moreover, Åland (Finland), Corse, Sardegna and Sicilia. Since the NUTS-2 region PT18 (Alentejo) has very minimal patent activities, this region has been aggregated with the region PT15 (Algarve) to one region in this study.

and six. n_i, s_i^K and s_i^H are averages for the period 1995-2003. We suppose that $g+\delta=0.05$, which is a fairly standard assumption in the literature (see among others, Mankiw, Romer and Weil 1992; Temple 1998; Durlauf and Johnson 1995; Ertur and Koch 2007; Fingleton and Fischer 2009). The main data source is Eurostat's Regio database. The data for Norway and Switzerland were provided by Statistics Norway and the Swiss Office Fédéral del Statistique, respectively.

The *N*-by-*N* technological weight matrix ***T*** measures the closeness of regions in a technological space spanned by *F*=120 distinct technology fields, described by the 120 patent classes of the International Patent Code (IPC) classification system at the second level[8]. We utilize corporate patents[9] applied at the European Patent Office (EPO) with an application date in the years 1990-1995 to define the technological position of a region, in terms of a *F*-by-1 vector where the *f*th element (*f*=1, …, *F*) denotes the share of patents in the *f*th IPC category. This definition reflects the region's diversity of inventive activities of its firms. A product moment correlation coefficient is used to measure the technological proximity between any two regions of the sample[10]. A high correlation indicates similarity and a low correlation dissimilarity. The matrix ***T*** was formed by using *m* regions that exhibited the highest correlation coefficients with each region *i*, for *i*=1, …, *N*.

6 Econometric results

Table 1 presents the estimation results[11], the estimated and implied parameters. We consider two model specifications. The first three columns of the table present the results based on the technological weight matrix with *m*=10 neighbours, the next three columns those based on the technological weight matrix with *m*=20 neighbours. The parameters obtained by ML estimation are given in the first and fourth columns, followed by the corresponding standard errors and the *p*-values. These parameters allowed us to calculate the output elasticity parameters α_K and α_H, and the implied value of ρ. To draw inferences regarding the statistical significance of these parameters we calculated measures of dispersion based on simulating parameters from the normally distributed parameters β_1, β_2, β_3, γ_1, γ_2, γ_3, λ, and σ_{ε}^2, using the estimated means and variance-covariance matrix. The simulated draws are then used in computationally efficient formulas to calculate the implied distribution of the output elasticity α_K and α_H, and the parameter ρ. Diagnostic tests were carried out for heteroskedasticity, using the spatial Breusch-Pagan test, and for normality, using the Jarque-Bera test. Performance of the model is expressed in terms of conventional statistical measures

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[8] The IPC system is an internationally agreed, non-overlapping hierarchical classification system that consists of eight sections (first level), 120 classes (second level), 628 subclasses (third level), 6,871 main classes (fourth level), and 57,324 subgroups (fifth level) to classify inventions claimed in the patent documents.

[9] It is beyond the scope of this paper to discuss all the problems invoked by the use of patents statistics (see Griliches 1990 for a discussion). But it should be noted that the range of patentable inventions constitutes only a subset of all R&D outcomes, and that patenting is a strategic decision and, thus, not all patentable inventions are actually patented. Therefore, patentability requirements and incentives to refrain from patenting limit our approach to measure the technological position of regions based on patent data.

[10] This measure is appealing because it allows for a continuous measure of technological distance by a simple transformation.

[11] We present only the unrestricted results, since the joint theoretical constraints, $\beta_1+\beta_2+\beta_3=0$ and $\gamma_1+\gamma_2+\gamma_3=0$, implied by constant returns are rejected by a likelihood ratio test.

of goodness of fit, such as the log likelihood value divided by *N* and the noise variance sigma square.

We note that the results do not differ greatly across the two model specifications. In fact, there are no statistically significant differences between the corresponding parameter estimates. The following aspects of the results are worth noting. *First*, all the parameter estimates that are significant have the predicted signs, with only one exception. The exception is the β_3 parameter estimate for population growth that is significant, but has an incorrect sign. The coefficients of physical capital and human capital (per worker) accumulation have the predicted signs. The latter, however, is only weakly significant and the effect is lower than expected. This may have different explanations. One is to point to the discrepancy between the theoretical variable representing human capital in the production function and the proxy used for investments in human capital in the empirical model specification. The educational attainment variable is a very partial measure of the ratio of investment in human capital, and, more important, does not account for regional differences in the quality of education.

Second, the elasticity of output with respect to the stock of physical capital, is very close to two-thirds, the upper bound generally admitted for this parameter. The implied value of α_H is negative, but insignificant.

Third, the coefficient ρ, measuring the degree of technological interdependence among regions, is very strong. The parameter estimate is 0.69 in the case of *m*=10 neighbours with a standard deviation of 0.18 (*p*=0.00) and 0.96 in the case of *m*=20 technological neighbours with a standard deviation of 0.24 (*p*=0.00). This result appears to show the importance of the technological interdependence between regions with similar technological profiles, and to provide evidence that technological proximity matters in the distribution of regional output in Europe. The implied values of θ and ϕ, not reported here, are not significant which indicates that local technological networks (as those defined within the regions) are not important for the diffusion of disembodied knowledge. This result may have different explanations. One is to point to the importance of European and national rather than local technological networks of the regions, along which disembodied knowledge seems to diffuse between firms.

But – as indicated in Section 4 – in order to avoid incorrect inferences, we need to interpret the significance and magnitude of the β- and γ-estimates and the implied value of ρ from our spatial Durbin model specification in light of the spatial structure. Table 2 presents the estimates for direct and indirect impacts of the MRW variables, and the implied value of ρ along with their associated statistics. A comparison of the direct impact estimates with the raw parameter estimates given in Table 1 shows that these two sets of estimates are similar in magnitude. The direct impact of the physical capital variable is slightly larger, while that of the human capital variable is somehow lower in the case of *m*=10 technological neighbours and slightly larger in the case of *m*=20. The difference between these estimates is due to feedback effects.

Table 1 Estimation results based on a spatial Durbin model specification using a technological weight matrix with m=10 and m=20 'technological neighbours' (unrestricted ML estimation, N=158)

	m=10 technological neighbours			m=20 technological neighbours		
	Coefficient	Std. dev.	p-value	Coefficient	Std. dev	p-value
Constant	7.002	2.585	p=0.007	3.814	3.480	p=0.273
$\ln s_i^K$ [β_1]	0.605	0.070	p=0.000	0.592	0.070	p=0.000
$\ln s_i^H$ [β_2]	0.062	0.037	p=0.089	0.065	0.038	p=0.084
$\ln(n_i+0.05)$ [β_3]	0.312	0.119	p=0.009	0.312	0.120	p=0.010
$\boldsymbol{T}\ln s_j^K$ [γ_1]	-0.766	0.275	p=0.005	-1.247	0.385	p=0.001
$\boldsymbol{T}\ln s_j^H$ [γ_2]	0.130	0.136	p=0.336	0.166	0.188	p=0.377
$\boldsymbol{T}\ln(n_j+0.05)$ [γ_3]	0.401	0.404	p=0.321	0.019	0.559	p=0.973
λ	0.501	0.145	p=0.000	0.499	0.189	p=0.009
Implied α_K	0.672	0.201	p=0.001	0.793	0.185	p=0.000
Implied α_H	-0.129	0.315	p=0.681	-0.113	0.140	p=0.420
Implied ρ	0.686	0.183	p=0.000	0.956	0.240	p=0.000
Diagnostics						
Heteroskedasticity (Breusch-Pagan)	3.852		p=0.697	8.523		p=0.202
Normality (Jarque-Bera)	52.227		p=0.001	44.965		p=0.001
Sigma square	0.0247			0.0250		
Log likelihood/N	0.7709			0.7681		

Notes: The rates s^K, s^H and n are averages over the time period 1995-2003; the dependent variable relates to 2004; standard errors and p-values of the implied values of α_K, α_H, and ρ are calculated using a simulation method (10,000 random draws)

The direct impact for $\ln s_i^K$ is 0.59 and that for $\ln s_i^H$ 0.07. This means that a one percent increase in physical capital and human capital investment will on average result in an increase of the future output by 0.59 and 0.07 percent, respectively.

Table 2 The spatial Durbin model specification (*m*=10 and *m*=20, technological neighbours, unrestricted ML estimation): Impact based interpretation of the estimation results

	m=10 technological neighbours			*m*=20 technological neighbours		
	Coefficient	Std. dev.	*p*-value	Coefficient	Std. dev.	*p*-value
Direct impacts						
$\ln s_i^K$	0.591	0.072	0.000	0.574	0.091	0.000
$\ln s_i^H$	0.067	0.039	0.081	0.069	0.040	0.088
$\ln(n_i + 0.05)$	0.329	0.123	0.007	0.315	0.125	0.012
Indirect impacts						
$\boldsymbol{T} \ln s_j^K$	-1.032	2.751	0.708	-2.184	8.873	0.806
$\boldsymbol{T} \ln s_j^H$	0.368	1.900	0.847	0.470	2.377	0.843
$\boldsymbol{T} \ln(n_j + 0.05)$	1.236	3.638	0.734	0.311	5.388	0.954
Implied ρ	0.706	0.832	0.489	1.394	5.413	0.797

Notes: To obtain the impact estimates we simulated 10,000 instances of $\boldsymbol{y}$, and estimated the parameters for the spatial Durbin model specification via maximum likelihood. Using the set of 10,000 estimates, we used LeSage and Pace's (2009) efficient formulas to compute the average direct and indirect impacts along with the standard deviation of the 10,000 outcomes. The table shows the average over the 10,000 impact estimates along with the associated standard deviation and *p*-values.

Turning to the indirect impact estimates we see that interpreting the estimates associated with the lagged variables as measures of the size and significance of indirect impacts in a spatial Durbin model specification would lead us to incorrect inferences about the presence or absence of physical capital externalities. The coefficient reported for physical capital accumulation is -0.766 with a standard deviation of 0.275 and highly significant (see Table 1), whereas the mean indirect impact for this variable is not significantly different from zero (see Table 2). Note that the presence or absence of significant physical capital externalities depends on whether the indirect effects that arise from changing region *i*'s physical capital results in statistically significant indirect effects.

The absence of both significant physical capital and human capital externalities among technologically similar regions implies that such regions are not technologically interdependent. The implied value of ρ that reflects the degree of interdependence is 0.71 in the case of *m*=10 and 1.39 in the case of *m*=20 technologically neighbouring regions, but both estimates are strongly insignificant (see Table 2).

7 Closing remarks

In this paper we considered a neoclassical growth model, which explicitly takes into account technological interdependence between technologically similar regions. Technological similarity is measured as closeness in technological space spanned by 120 technological fields. The transition from theory to econometrics leads to a reduced-form empirical model that in the spatial econometrics literature is known as spatial Durbin model specification.

The paper illustrates the importance of an impact-based model interpretation, in terms of the LeSage and Pace (2009) approach, to correctly quantify the magnitude of spillover effects in order to avoid incorrect inferences about the presence or absence of capital externalities and the "true" role technological interdependence among regions with similar technological profiles play in growth processes in Europe.

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