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REGIONS, TECHNOLOGICAL INTERDEPENDENCE AND GROWTH IN EUROPE

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Biographical note

Manfred M. Fischer (1947) is professor of economic geography at the Vienna University of Economics and BA. His research interests, encompassing a wide variety of subject areas including economic geography, regional economics and regional science, innovation economics, geocomputation and spatial analysis, spatial econometrics, geographic information science, regional housing and labour markets, transportation and GIS-T. In all these fields he has widely published: 31 books, 93 articles in academic journals, and 105 book chapters. He has been advisor to the Commission of the European Union, several granting agencies and universities around the world. Manfred was the co-founder of the prominent geographical journal Geographical Systems and is editor-in-chief of its successor, the Journal of Geographical Systems. In addition, he is co-founder of the most prominent regional science book series Advances in Spatial Science. He has been visiting professor at several universities including the University of California at Santa Barbara and the Oskar Lange Academy of Economics in Poland. He is fellow of the International Eurasian Academy of Sciences, the Royal Dutch Academy of Sciences, the World Academy of Arts and Sciences and the Regional Science Association International, and corresponding member of the Austrian Academy of Sciences.

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 spatial externalities caused by disembodied knowledge diffusion between technologically similar regions. The transition from theory to econometrics yields a reduced-form empirical model that in the 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 that avoid incorrect inferences about the presence or absence of significant capital externalities among technologically similar regions.

JEL Classification: C31, O18, O47, R11

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Introduction

Neoclassical growth theory traditionally has treated each region as if it were an island onto itself. If ever this practice was defensible, surely it is no longer at least in Europe. The increased exchange of goods and ideas has fostered an increasing interdependence among regions' technological fortunes and long-term performances.

This paper presents an open-economy extension of the Mankiw-Romer-Weil (henceforth MRW) model by explicitly accounting for technological interdependence among the economies. The objective of the model is to explain interregional differences in output per worker. Output is produced from physical capital, human capital and labour, and used for investments in physical and human capital and consumption. The regional economies evolve independently in all respects except for technological interdependence. The paper departs from previous work of the author (see Fischer 2009) by shifting attention from the geographic to the technological component to the knowledge spillover mechanism.

According to this view, the ability of a region to make productive use of another region's 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 remainder of the paper is organized 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 while section 4 outlines the relevant estimation approach.

The inherent complexity of the spatial Durbin model specification implies that treating the parameter estimates like least-squares parameter estimates is incorrect, as noted by LeSage and Fischer (2008). 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 5 describes LeSage and Pace's (2009) computational approach to calculating scalar summary measures of these impacts. In Section 6, we describe the data and the construction of the connectivity matrix that represents the technological closeness between the regions in the sample. Section 7 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 spatial capital externalities and the degree of interdependence among technologically similar regions in particular. Section 8 concludes the paper.

1. 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.

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 and regions.

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[1] 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 a common knowledge base which is immediately available for use in any regional 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[2].

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

[1] Note that Ertur and Koch (2007) used this same kind of formulation to model technological interdependence in a Solow world of countries.

[2] 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.

on the right hand side of Eq. (5) represents the 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 region *i* to regions *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 $\Sigma_{j \ne i} T_{ij} = 1$ for $i = 1, ..., N$, and may be organized to form a technological connectivity matrix $\boldsymbol{T}$, 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 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

$$y_{it} = \boldsymbol{\Omega}_i^{\frac{1}{1-\rho}} \; k_{it}^{u_{ii}} \; h_{it}^{v_{ii}} \prod_{j \ne i}^{N} k_{jt}^{u_{ij}} \; h_{jt}^{v_{ij}} \tag{6}$$

with

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

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

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

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

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[3].

[3] Note that $(\boldsymbol{I} - \rho \boldsymbol{T})^{-1} = \Sigma_{r=0}^{\infty} (\rho \boldsymbol{T})^r = \Sigma_{r=0}^{\infty} \rho^r (\boldsymbol{T}^r)$, $\Sigma_{r=0}^{\infty} \boldsymbol{T}^r$ is row standardized since $\boldsymbol{T}$ is so, $\Sigma_{r=0}^{\infty} \boldsymbol{T}^r \boldsymbol{\Omega} = \boldsymbol{\Omega}$, $\Sigma_{r=0}^{\infty} \rho^r = 1/(1-\rho)$ if $|\rho| < 1$.

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

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

with $\eta=\alpha_K+\alpha_H+\theta+\phi$ and the balanced growth[4] rate $g=\mu[(1-\rho)(1-\alpha_K- \quad -\alpha_H)-\theta-\phi]^{-1}$. 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 growth model has the same qualitative predictions as the MRW model. Equation (11) states that a region i will have higher per worker output at a point in time (in the steady state) the higher is its own physical capital investment rate $(\ln s_i^K)$, the higher is its own human capital investment rate $(\ln s_i^H)$ and the lower is its population growth rate $\ln(n_i+g+\delta)$. Per worker output of region i 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)].

2. Model specification

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

[4] 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.

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

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[5]. 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 technologically 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 contains a linear combination of the per worker output levels from technologically neighbouring regions, those identified by $T_{ij} > 0$,

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

$\boldsymbol{\iota}_N$ 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: $\boldsymbol{\varepsilon} \sim N\ (\boldsymbol{0}, \sigma^2 \boldsymbol{I})$.

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[5] The term $\boldsymbol{\Omega}_0$ reflects – as Mankiw, Romer and Weil (1992) emphasize – not just technology, but also idiosyncratic regional characteristics such as resource endowments, institutions etc.

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 denotes the technological interdependence between the regions and defines the difference to a MRW world of closed regions.

3. Model estimation

In the spatial econometrics literature, a model specification like Eq. (13) is referred to as a spatial Durbin model (SDM). 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 maximum likelihood estimates can be found using the log-likelihood function concentrated with respect to the coefficient vector $\boldsymbol{\delta} = [\beta_0, \boldsymbol{\beta}, \boldsymbol{\gamma}]'$ and the noise parameter σ^2 and reducing[6] maximum likelihood to a univariate optimization problem in the parameter λ

$$\ln \mathcal{L}(\lambda) = C + \ln |\boldsymbol{I}_N - \lambda \boldsymbol{T}| - \frac{N}{2} \ln[S(\lambda)] \tag{14}$$

with

$$S(\lambda) = \boldsymbol{e}(\lambda)' \, \boldsymbol{e}(\lambda) = \boldsymbol{e}'_o \, \boldsymbol{e}_o - 2\lambda \, \boldsymbol{e}'_o \, \boldsymbol{e}_d + \lambda^2 \boldsymbol{e}'_d \, \boldsymbol{e}_d \tag{15}$$

$$\boldsymbol{e}(\lambda) = \boldsymbol{e}_o - \lambda \boldsymbol{e}_d \tag{16}$$

$$\boldsymbol{e}_o = \boldsymbol{y} - \boldsymbol{Z}\boldsymbol{\delta}_o \tag{17}$$

$$\boldsymbol{e}_d = \boldsymbol{Ty} - \boldsymbol{Z}\boldsymbol{\delta}_d \tag{18}$$

$$\boldsymbol{\delta}_o = (\boldsymbol{Z}'\,\boldsymbol{Z})^{-1}\boldsymbol{Z}'\,\boldsymbol{y} \tag{19}$$

$$\boldsymbol{\delta}_d = (\boldsymbol{Z}'\,\boldsymbol{Z})^{-1}\boldsymbol{Z}'\boldsymbol{Ty} \tag{20}$$

where the notation $\boldsymbol{e}(\lambda)$ is used to indicate that this vector depends on values taken by the parameter λ, as does the scalar concentrated log-likelihood function value $\ln \mathcal{L}(\lambda)$. $\boldsymbol{Z} = [\boldsymbol{\iota}_N \; \boldsymbol{X} \; \boldsymbol{TX}]$ and C is a constant not involving the parameters.

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

[6] Note that the scalar moments $\boldsymbol{e}'_o\boldsymbol{e}_o$, $\boldsymbol{e}'_o\boldsymbol{e}_d$ and $\boldsymbol{e}'_d\,\boldsymbol{e}_d$ and the Q-by-1 vectors $\boldsymbol{\delta}_o$ and $\boldsymbol{\delta}_d$ are computed prior to optimization, and so given a value for λ, calculating $S(\lambda)$ simply requires weighting three numbers (LeSage and Pace 2009). We used the simplex optimization algorithm to solve the univariate optimization problem.

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 $\boldsymbol{X}_q$ (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 $S_q(T)_{ii}$, which equals $N^{-1}tr(S_q(\boldsymbol{T}))$ where $S_q(T)_{ii}$ is the (*i*, *i*)th element of the *N*-by-*N* matrix

$$S_q(\boldsymbol{T}) = (\boldsymbol{I}_N - \lambda \boldsymbol{T})^{-1}(\boldsymbol{I}_N \beta_q + \boldsymbol{T}\gamma_q) \qquad (21)$$

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

(i)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 $S_q(\boldsymbol{T})$ given by Eq. (21). 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.

There is no clear-cut definition of how human capital should be represented and measured. In this study, we use 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 and six.

n_i, s_i^K and s_i^H are averages for the period 1995-2003. Following standard practice, we assume that $g+\delta=0.05$ (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 de la Statistique, respectively.

The N-by-N technological weight matrix $\boldsymbol{T}$ measures the closeness of regions in a technological space spanned by F=120 distinct technology fields, described by the 120 patent classes of the

[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.

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 fth element (f=1, …, F) denotes the share of patents in the fth 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 $\boldsymbol{T}$ 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 point estimates obtained by maximum likelihood estimation are given in the first and fourth columns, followed by the corresponding standard deviations and the p-values. These parameter estimates 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 $\beta_1, \beta_2, \beta_3, \gamma_1, \gamma_2, \gamma_3, \lambda,$ and σ_{ε}^2, using the estimated means and variance-covariance matrix. The simulated draws were then used in computationally efficient formulas to calculate the implied distribution of the output elasticities 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 models is expressed in terms of conventional statistical measures of goodness of fit, such as the log-likelihood value divided by N, and the noise variance sigma square.

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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.

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	0.672	0.201	p=0.001	0.793	0.185	p=0.000
Implied α	-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 deviations and p-values of the implied values of α_K, α_H, and ρ are calculated using a simulation method (10,000 random draws)

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 rate 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 emphasized in Section 5, it is necessary to calculate the direct and indirect effects associated with changes in the MRW determinants on regional output to arrive at a correct interpretation of the model. Table 2 presents the corresponding impact estimates, along with their associated statistics. A comparison of the direct impact estimates in Table 2 and the SDM coefficient estimates in Table 1 shows that these two sets of estimates are not so dissimilar in magnitude. The direct impact estimate of the human capital variable is slightly larger, while that of the physical capital variable is somewhat lower than one would infer from the SDM coefficient estimates (unconstrained estimation). The difference between these estimates is due to feedback estimates.

Since our empirical model is specified by using a log-transformation of both the dependent and independent variables the direct impact estimates can be interpreted as elasticities. Based on the positive 0.591 estimate for the direct impact estimate of the physical capital determinant and the positive 0.067 estimate for the direct impact estimate of the human capital determinant (*m*=10), we would conclude that a ten percent increase in regional physical (human) capital investment would result in a 5.9 (0.7) percent increase in regional output, and these increases are statistically significant.

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 deviations and *p*-values.

The indirect impact estimates are what economists usually refer to as cross-region spillovers. The presence or absence of significant spillovers across technologically neighbouring regions depends on whether the indirect effects that arise from changing region *i*'s MRW variables results in statistically significant indirect effects. We emphasize that it would be a mistake to interpret the SDM coefficient estimates $\gamma_q\ (q=1, ..., 3)$ as representing cross-region spillover magnitudes.

To see how incorrect this is, consider the difference between the lag coefficient γ_1 for the physical capital investment rate from the SDM model (reported in Table 1) and the indirect impact estimate calculated from the partial derivatives of the model (reported in Table 2). We see that the SDM coefficient associated with the lag variable $\boldsymbol{T} \ln s_j^k$ is -0.766 (standard deviation: 0.275) and statistically significant (p=0.005). The indirect impact is -1.032, but not significantly different from zero, based on the p-value (p=0.708). If we would incorrectly view the SDM coefficient estimate γ_1 on the lag of $\ln s_j^k$ as reflecting the indirect impact, this would lead to an inference that the physical capital variable in technologically neighbouring regions exerts a negative and significant indirect impact on regional output. But the true impact estimate points to the absence of physical capital spillovers among technologically neighbouring regions.

7. Closing remarks

In this paper we have suggested an open-economy extension of the Mankiw-Romer-Weil model for explaining interregional differences in output per worker. Output is produced from physical capital, human capital and labour, and used for investments in physical and human capital, and consumption. The regional economies evolve independently in all respects except for technological interdependence. Technological interdependence is assumed to work through spatial externalities caused by disembodied knowledge diffusion across technologically similar regions.

The theoretical model and the associated reduced-form empirical SDM model both imply a non-independent relationship between changes in region *j*'s physical and human capital or population growth rates and region *i*. A correct interpretation of the model parameters, in terms of the LeSage and Pace (2009) approach, point to the absence of both physical and human capital externalities across technologically similar regions. This result implies that the technological dimension to the spillover mechanism does not play a significant role for the diffusion of disembodied knowledge in regional growth processes in Europe.

It is important to note, however, that the inferences were made conditional on the specification of the technological weight matrix, and the technological space described by 120 patent classes might be too crude to appropriately capture capital externalities across technologically similar regions.

Further research appears to be necessary to investigate more deeply the role played by the technological dimension of the diffusion process of disembodied knowledge in regional growth processes.

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