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# **Cross-region knowledge spillovers and total factor productivity.**

## **European evidence using a spatial panel data model**

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**Abstract.** This paper concentrates on the central link between productivity and knowledge capital, and shifts attention from firms and industries to regions. The objective is to measure knowledge elasticity effects within a regional Cobb-Douglas production function framework, with an emphasis on knowledge spillovers. The analysis uses a panel of 203 European regions to estimate the effects over the period 1997-2002. The dependent variable is total factor productivity (TFP). We use a region-level relative TFP index as an approximation to the true TFP measure. This index describes how efficiently each region transforms physical capital and labour into outputs. The explanatory variables are internal and out-of-region stocks of knowledge, the latter capturing the contribution of interregional knowledge spillovers. We use patents to measure knowledge capital. Patent stocks are constructed such that patents applied at the European Patent Office in one year add to the stock in the following and then depreciate throughout the patents effective life according to a rate of knowledge obsolescence. A random effects panel data spatial error model is advocated and implemented for analyzing the productivity effects. The findings provide a fairly remarkable confirmation of the role of knowledge capital contributing to productivity differences among regions, and adding an important dimension to the discussion, showing that knowledge spillover effects increase with geographic proximity.

**Keywords.** Total factor productivity, knowledge spillovers, European regions, panel data, spatial econometrics

**JEL Classification.** C23, O49, O52, R15

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## 1 Introduction

Many economic studies, such as the pioneering study by Solow (1957), have demonstrated the central role played by technological progress in economic growth. These studies which are based on a growth-accounting approach do not attempt to measure technological progress directly, but treat it as the residual factor accounting for growth. According to the standard interpretation, this residual represents disembodied technological progress, usually referred to as total factor productivity (TFP).

In an attempt to overcome the measurement difficulties inherent in an encompassing definition of technological progress, economists have focused attention on R&D – viewed as a relatively clearly defined set of activities – that contribute both directly and indirectly to changes in products and production processes (Mairesse and Sassenou 1991). Interest in empirical research into the relationship between R&D and total factor productivity was prompted by the productivity slowdown observed in much of the industrialized world in the 1970s (Griliches 1986). Most of these studies rely on the Cobb-Douglas production function as their basic analytical framework and relate measures of output or TFP (or their rates of growth), across firms or industries, to measures of R&D capital or intensity of R&D investment.

A smaller subset of such studies also includes measures of “external” R&D capital in an attempt to estimate the productivity effects of knowledge spillovers across firms<sup>1</sup> (see Los and Verspagen 2000, Griliches and Mairesse 1984), across industries (see, for example, Verspagen 1997, Goto and Suzuki 1989, Griliches and Lichtenberg 1984) or across countries<sup>2</sup> (see, for example, Gong and Keller 2003, Coe and Helpman 1995, Park 1995). Measuring knowledge spillovers and their productivity effects at the regional level remains a less explored area<sup>3</sup>, even though the regional dimension is particularly relevant at the European level.

We know that knowledge is an input in regional production that bears some peculiar properties. It is a non-rival input in the creation of new knowledge. The use of an idea to produce goods by an agent does not preclude any other individual to build on it in order to generate a new one (Romer 1990). Secrecy is certainly a way to prevent knowledge diffusion and it is often used by

firms to exclude others from the use of novel ideas. But even in the case of a patent, that is made public, the research that leads to it and the background ideas may be kept known only to a restricted number of people, at least for a while as Bottazzi and Peri (1999) argue. This partial non-excludability of knowledge suggests that R&D may create benefits to firms and individuals external to the inventor by adding to their knowledge base. These benefits are usually termed knowledge spillovers<sup>4</sup>.

The objective of our study is to estimate the impact of cross-region knowledge spillovers on total factor productivity in Europe. By Europe we mean the 15 pre-2004 EU member states. We use a panel of 203 NUTS-2 regions to estimate the impact over the period 1997-2002. NUTS-2 regions are interesting units of analysis in an increasingly integrated European market. They are more homogeneous than countries, better connected within themselves, and they are becoming increasingly important as policy units for research and innovation (see European Commission 2001). The study departs from previous research not only by shifting attention from industries to regions, but also adds an important dimension to the discussion by showing that productivity effects of knowledge spillovers increase with geographic proximity. It implements a random effects panel data regression model with spatial autocorrelation to estimate the effects using patent applications as a measure of R&D output to capture the contribution of R&D (direct and spilled-over) to regional productivity.

The remainder of the paper is organized as follows. The section that follows presents the empirical model which relates the region's knowledge stock and its external stock of knowledge to productivity within a regional Cobb-Douglas production function framework. We use a region level relative TFP index as an approximation to the true TFP measure and patent stocks to proxy knowledge capital stocks. Section 3 provides details on the construction of both, the TFP index and the patent stocks. Important econometric issues raised by the estimation of productivity effects of interregional knowledge spillovers are addressed in Section 4, while Section 5 reports the estimation results. Some conclusions of the study are to be found in the last section of the paper.

## 2 The empirical model

We follow the research tradition that finds thinking in terms of a regional production function congenial and useful. Less “neoclassical” oriented economists might deny the usefulness of this view or the simplifications on which this view is based. But we believe that the importance and extent of cross-region knowledge spillovers can be best discussed in the context of an expanded version of the standard regional Cobb-Douglas production function that treats knowledge as another type of capital added to conventional aggregate production function variables. Passing over a long list of conceptual and empirical problems associated with the concept of knowledge capital (for a discussion see Griliches 1979) we can write this regional production function as

$$Q_{it} = L_{it}^{\alpha} C_{it}^{\beta} K_{it}^{\gamma_1} K_{it}^{*\gamma_2} \exp(\varepsilon_{it}) \quad i = 1, \dots, N; t = 1, \dots, T \quad (1)$$

where  $Q$  is some measure of output for region  $i$  at time  $t$ .  $L$  stands for the labour stock of the region,  $C$  is a measure of the physical capital stock,  $K$  is the region-internal and  $K^*$  is the region-external (out-of-region) stock of knowledge.  $\alpha$ ,  $\beta$ ,  $\gamma_1$  and  $\gamma_2$  are the elasticities of output with respect to labour, physical capital, region-internal and region-external knowledge capital.  $\varepsilon$  is the error term reflecting the effects of unknown factors, approximations, and other disturbances.

Dividing Equation (1) by factor share weighted physical capital and labour inputs, yields the empirical model to be estimated

$$f_{it} = \gamma_1 k_{it} + \gamma_2 k_{it}^* + \varepsilon_{it} \quad i = 1, \dots, N; t = 1, \dots, T \quad (2)$$

where all terms are expressed in logarithms. Equation (2) relates the region’s knowledge stock and its external stock of knowledge to productivity in a reduced-form framework. The variable  $f_{it}$  is the TFP level of region  $i$  at time  $t$ ,  $k_{it}$  is region’s  $i$  knowledge stock at time  $t$  and  $k^*$  is its external stock of knowledge. The  $\gamma_1$  and  $\gamma_2$  are parameters to be estimated, and  $\varepsilon_{it}$  is an error term with properties we discuss below.  $\gamma_1$  measures the (elasticity) effect of the knowledge stock on productivity, while  $\gamma_2$  captures the relative (elasticity) effect from foreign stocks of knowledge. A positive and significant  $\gamma_2$  is interpreted as evidence of cross-region knowledge spillovers.

In this study,  $k_{it}^*$ , the term representing the spillover knowledge stock is defined as a spatially discounted sum of the internal knowledge stocks of all other regions  $j \neq i$ , i.e.,

$$k_{it}^* = \sum_{j \neq i}^N \exp(-\delta d_{ij}) k_{jt} \quad i = 1, \dots, N; t = 1, \dots, T \quad (3)$$

where  $d_{ij}$  denotes the distance from region  $i$  to  $j$  measured in terms of the great circle distance between the regions' economic centres. This definition assumes that the closer regions are in geographic space, the more they can gain from each other's research efforts.  $\delta \geq 0$  is the distance (decay) parameter that captures the degree of localization of cross-region knowledge spillovers. Estimating  $\delta = 0$  would mean that distance does not matter, while positive estimates of  $\delta$  suggest that the benefits for other regions' knowledge stocks are decreasing with distance. Note that the effective knowledge contribution by region  $j$  depends parametrically on an exponential functional form between that region and region  $i$ .

### 3 Empirical setting and data description

This section takes a look at the data we will employ, describes the construction of the knowledge capital stock variables, and the total factor productivity index that is used to register the impact of direct and indirect knowledge capital stocks. Our data form a combined time-series cross-section panel. The panel database is composed of 203 regions, over the period 1990-2002. The data come from two major sources: Information used to construct the TFP index comes from the Cambridge Econometrics database, while the European Patent Office patent database is the source for constructing patent stocks to proxy knowledge stocks.

*Units of observation:* The observations units are NUTS-2 regions that are adopted by the European Commission for their evaluation of regional growth processes. The NUTS-2 region, although varying considerably in size, is widely viewed as the most appropriate unit for modelling and analysis purposes (see, e.g., Fingleton 2001). The cross-section is composed of 203 NUTS-2 regions located in the 15 pre-2004 EU member states. We exclude the Spanish

North African territories of Ceuta and Melilla, and the French Départments d'Outre-Mer Guadeloupe, Martinique, French Guayana and Réunion. The Appendix describes the sample of regions.

*Measurement of total factor productivity:* There are many ways of measuring total factor productivity (see Nadiri 2001). But the measure suggested by Caves, Christensen and Diewert (1982) seems to be most appropriate for the purpose of our study<sup>5</sup>. The index is defined as

$$\log F_{it} = (\log Q_{it} - \overline{\log Q_t}) - s_{it}(\log L_{it} - \overline{\log L_t}) - (1 - s_{it})(\log C_{it} - \overline{\log C_t}) \quad (4)$$

for  $i = 1, \dots, N$  and  $t = 1, \dots, T$ , where the variable  $Q$  is value-added,  $L$  is labour input, and  $C$  denotes physical capital input as above.  $s_{it}$  is the share of labour in total production costs, while the terms  $\overline{\log Q_t}$ ,  $\overline{\log L_t}$  and  $\overline{\log C_t}$  are given by

$$\overline{\log Q_t} = \frac{1}{N} \sum_{i=1}^N \log Q_{it} \quad t = 1, \dots, T \quad (6)$$

$$\overline{\log L_t} = \frac{1}{N} \sum_{i=1}^N \log L_{it} \quad t = 1, \dots, T \quad (6)$$

$$\overline{\log C_t} = \frac{1}{N} \sum_{i=1}^N \log C_{it} \quad t = 1, \dots, T. \quad (7)$$

This index assumes that production is characterized by constant returns to scale. It provides a measure of each region's productivity relative to the other  $N-1$  regions and is equivalent to an output index where labour and physical capital inputs are held constant across regions. Thus, it describes how efficiently each region transforms labour and physical capital into outputs. To provide a simple illustration, if a region's TFP level is computed as 1.2, this implies that the region can produce 20 percent more output than the average region, with the same amount of conventional inputs.

Gross value added data in Euro (constant prices of 1995, deflated) has been used as measure of output  $Q$ . Building on the work by Keller (2002) we have used cost-based rather than revenue-

based factor shares to construct the index. Cost-based shares are more robust in the presence of imperfect competition. Two other important characteristics of the TFP data are: First, we adjusted the Cambridge Econometrics data on labour inputs to account for differences in average annual hours worked across countries. This is important because average annual hours worked in the year 1997 in Swedish manufacturing for example, were almost 14 percent lower than in Greek manufacturing. Without adjusting for differences in input usage, productivity in Greek and Portuguese regions would be overestimated throughout, while in Swedish and Dutch regions underestimated.

Second, physical capital stock data is not available in the Cambridge Econometrics database, but gross fixed capital formation in current prices is. Thus, we generate the fixed capital stocks by using the perpetual inventory method. The annual flows of fixed investments are deflated by national gross fixed capital formation deflators. This computation of  $C$  implies that the stock of fixed capital depends on the assumed depreciation rate and on the annual rate of growth of investments during the period preceding the first year of evaluation of the stock. We apply a constant rate of ten percent depreciation across space and time. The mean annual rate of growth, which precedes the benchmark year 1997, covers the period 1990-1997.

*Measurement of knowledge capital stocks:* A number of proxies can be used for knowledge capital, including stocks of R&D expenditure, data on actual innovations and patent counts. R&D expenditure is the most common choice, but suffers from the problem of double counting because of special fiscal rules in favour of R&D spending. As the necessary data for adjustment are not available double counting cannot be corrected for here.

Thus, in this study we use patent counts as a proxy for the increase in (economically profitable) knowledge. Patents have the comparative advantage of being direct outcome of R&D processes. The patent data are numbers of corporate patent applications. Corporate patents cover inventions of new and useful processes, machines, manufactures, and compositions of matter. To the extent that patents document inventions, an aggregation of patents is arguably more closely related to a stock of knowledge than is an aggregation of R&D expenditures (Robbins 2006). However, a well known problem of using patent data is that technological inventions are not all patented. This could be because of applying for a patent, is a strategic decision and, thus, not all patentable



inventions are actually patented. Even if this is not an issue, as long as a large part of knowledge is tacit, patent statistics will necessarily miss that part, because codification is necessary for patenting to occur. We assume that part of the knowledge generated with the idea leading to a patent is embodied in persons, imperfectly codified, and linked to the experience of the inventor(s). This stock of knowledge increases in a region as local inventors discover new ideas. It diffuses mostly via face-to-face interactions. Following Bottazzi and Peri (2003) we think of it as a local public good as it benefits researchers within the region and its neighbourhood.

Patent stocks were derived from European Patent Office (EPO) documents. Each EPO document provides information on the inventor(s), his or her name and address, the company or institution to which property rights have been assigned, citations to previous patents, and a description of the device or process. To create the patent stocks for 1997-2002, the EPO patents with an application date 1990-2004 were transformed from individual patents into stocks by first sorting based on the year that a patent was applied for, and second the region where the inventors resides. In the case of cross-region inventor teams we used the procedure of fractional counting<sup>6</sup>. Then for each region, the annual patents were aggregated using the perpetual inventory method, with a constant 12 percent depreciation rate<sup>7</sup> applied for each year to the stock of patents created in earlier years. Thus, the region-internal knowledge stocks,  $k_{it}$  ( $i=1,\dots,N; t=1,\dots,T$ ), are depreciated sums over time of patents applied by inventors in region  $i$ , while the out-of-region knowledge stocks,  $k_{it}^*$  ( $i=1,\dots,N; t=1,\dots,T$ ), are depreciated sums over time of patents applied by inventors in other regions  $j$  excluding  $i$ .

#### 4 Error specification and model estimation

We now turn to the estimation of the reduced-form model given by Equations (2)-(3) that can be rewritten in matrix notation as

$$\mathbf{f} = \mathbf{X}\boldsymbol{\gamma} + \boldsymbol{\varepsilon} \tag{8}$$

where  $\mathbf{f}$  is of dimension  $NT$ -by-1,  $\mathbf{X}$  is  $NT$ -by-2,  $\boldsymbol{\gamma}$  is 2-by-1 and  $\boldsymbol{\varepsilon}$  is  $NT$ -by-1. The observations are ordered with  $t$  being the slow running index and  $i$  is the fast running index<sup>8</sup>, i.e.,  $\mathbf{f} = (f_{11}, \dots, f_{N1}, \dots, f_{1T}, \dots, f_{NT})'$ .

The disturbance vector of Equation (8) is assumed to follow an error component model<sup>9</sup> with random region effects and spatially autocorrelated residuals (see Anselin 1988, pp. 152). The disturbance vector for time  $t$  is given by

$$\boldsymbol{\varepsilon}_t = \boldsymbol{\mu} + \boldsymbol{\zeta}_t \quad (9)$$

with

$$\boldsymbol{\zeta}_t = \lambda \mathbf{W} \boldsymbol{\zeta}_t + \boldsymbol{\eta}_t \quad (10)$$

where  $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \dots, \varepsilon_{Nt})'$ ,  $\boldsymbol{\zeta}_t = (\zeta_{1t}, \dots, \zeta_{Nt})'$ , and  $\boldsymbol{\mu} = (\mu_1, \dots, \mu_N)'$  denotes the vector of random region effects<sup>10</sup> which are assumed to be *iid*  $(0, \sigma_\mu^2)$ .  $\boldsymbol{\eta}_t = (\eta_{1t}, \dots, \eta_{Nt})$  where  $\eta_{it}$  is *iid* over  $i$  and  $t$  and is assumed to be  $\mathcal{N}(0, \sigma_\eta^2)$ . The  $\{\eta_{it}\}$  process is also independent of the process  $\{\mu_i\}$ .  $\lambda$  is the scalar spatial autoregressive coefficient with  $|\lambda| < 1$ .  $\mathbf{W}$  is a known  $N$ -by- $N$  spatial weights matrix where diagonal elements are zero. In this study, the weights matrix is constructed so that a neighbouring region takes the value of one and zero otherwise. The rows of this matrix are normalized<sup>11</sup> by the largest characteristic root of  $\mathbf{W}$ . Thus, the matrix  $(\mathbf{I}_N - \lambda \mathbf{W})$  is non-singular, where  $\mathbf{I}_N$  is an identity matrix of dimension  $N$ . We note that for  $T = 1$  our specification reduces to the standard Cliff-Ord first order spatial autoregressive model.

Let  $\mathbf{A} = \mathbf{A}(\lambda) = \mathbf{I}_N - \lambda \mathbf{W}$ , then the disturbances in Equation (10) can be written as follows:

$$\boldsymbol{\zeta}_t = (\mathbf{I}_N - \lambda \mathbf{W})^{-1} \boldsymbol{\eta}_t = \mathbf{A}^{-1} \boldsymbol{\eta}_t. \text{ Substituting } \boldsymbol{\zeta}_t \text{ in Equation (9), we get}$$

$$\boldsymbol{\varepsilon} = (\mathbf{1}_T \otimes \mathbf{I}_N) \boldsymbol{\mu} + (\mathbf{I}_T \otimes \mathbf{A}^{-1}) \boldsymbol{\eta} \quad (11)$$

where  $\boldsymbol{\eta}' = (\eta'_1, \dots, \eta'_T)$ ,  $\mathbf{1}_T$  is a vector of ones of dimension  $T$ ,  $\mathbf{I}_T$  is an identity matrix of dimension  $T$  and  $\otimes$  denotes the Kronecker product. Under these assumptions, the variance-covariance matrix<sup>12</sup> for  $\boldsymbol{\varepsilon}$  can be written as

$$\boldsymbol{\Omega}_\varepsilon = E[\boldsymbol{\varepsilon} \boldsymbol{\varepsilon}'] = \sigma_\mu^2 (\mathbf{J}_T \otimes \mathbf{I}_N) + \sigma_\eta^2 [\mathbf{I}_T \otimes (\mathbf{A}'\mathbf{A})^{-1}] \quad (12)$$

where  $\mathbf{J}_T$  is a matrix of ones of dimension  $T$ , and  $\mathbf{J}_T = \mathbf{1}_T \mathbf{1}_T'$ . Following Baltagi, Song and Koh (2003), this variance-covariance matrix can be rewritten as

$$\boldsymbol{\Omega}_\varepsilon = \sigma_\eta^2 [\bar{\mathbf{J}}_T \otimes (T\phi \mathbf{I}_N + (\mathbf{A}'\mathbf{A})^{-1}) + \mathbf{E}_T \otimes (\mathbf{A}'\mathbf{A})^{-1}] = \sigma_\eta^2 \boldsymbol{\Sigma}_\varepsilon \quad (13)$$

where  $\phi = \sigma_\mu^2 / \sigma_\eta^2$ ,  $\bar{\mathbf{J}}_T = \mathbf{J}_T / T$ ,  $\mathbf{E}_T = \mathbf{I}_T - \bar{\mathbf{J}}_T$ , and  $\boldsymbol{\Sigma}_\varepsilon = [\bar{\mathbf{J}}_T \otimes (T\phi \mathbf{I}_N + (\mathbf{A}'\mathbf{A})^{-1}) + \mathbf{E}_T \otimes (\mathbf{A}'\mathbf{A})^{-1}]$ .

Using results from Wansbeek and Kapteyn (1983),  $\boldsymbol{\Sigma}_\varepsilon^{-1}$  is given by

$$\boldsymbol{\Sigma}_\varepsilon^{-1} = \bar{\mathbf{J}}_T \otimes (T\phi \mathbf{I}_N + (\mathbf{A}'\mathbf{A})^{-1})^{-1} + \mathbf{E}_T \otimes (\mathbf{A}'\mathbf{A}) \quad (14)$$

which involves no matrix inversions of dimension larger than  $N$ . Also,  $|\boldsymbol{\Sigma}_\varepsilon| = |T\phi \mathbf{I}_N + (\mathbf{A}'\mathbf{A})^{-1}| |(\mathbf{A}'\mathbf{A})^{-1}|^{T-1}$ . Under the assumption of normality, the log-likelihood for this model, conditional on  $\delta$ , can be derived (see Anselin 1988, pp. 154, Elhorst 2003) as

$$\begin{aligned} \mathcal{L}(\boldsymbol{\gamma}, \sigma_\eta^2, \phi, \lambda | \delta) &= -\frac{NT}{2} \log(2\pi \sigma_\eta^2) - \frac{1}{2} \log |\boldsymbol{\Sigma}_\varepsilon(\phi, \lambda)| - \frac{1}{2\sigma_\eta^2} \mathbf{e}'(\delta) \boldsymbol{\Sigma}_\varepsilon^{-1}(\phi, \lambda) \mathbf{e}(\delta) = \\ &= -\frac{NT}{2} \log(2\pi \sigma_\eta^2) - \frac{1}{2} \log \left| T\phi \mathbf{I}_N + \left[ \mathbf{A}'(\lambda) \mathbf{A}(\lambda)^{-1} \right] \right| + \\ &\quad + \frac{T-1}{2} \log \left| \mathbf{A}'(\lambda) \mathbf{A}(\lambda)^{-1} \right| - \frac{1}{2\sigma_\eta^2} \mathbf{e}'(\delta) \boldsymbol{\Sigma}_\varepsilon^{-1}(\phi, \lambda) \mathbf{e}(\delta) \end{aligned} \quad (15)$$

where  $\mathbf{e}(\delta) = (\mathbf{f} - \mathbf{X}(\delta)\boldsymbol{\gamma})$ . The parameters  $\boldsymbol{\gamma}$  and  $\sigma_\eta^2$  can be solved from first-order maximizing conditions

$$\hat{\boldsymbol{\gamma}}(\phi, \lambda | \delta) = \left\{ \mathbf{X}(\delta) [\boldsymbol{\Sigma}_\varepsilon(\phi, \lambda)]^{-1} \mathbf{X}(\delta) \right\}^{-1} \mathbf{X}'(\delta) \boldsymbol{\Sigma}_\varepsilon(\phi, \lambda) \mathbf{f} \quad (16)$$

$$\hat{\sigma}_\eta^2(\phi, \lambda | \delta) = \frac{1}{NT} \mathbf{e}'(\delta) [\boldsymbol{\Sigma}_\varepsilon(\phi, \lambda)]^{-1} \mathbf{e}(\delta) \quad (17)$$

which are functions that maximize the concentrated log-likelihood function, concentrating out the  $\boldsymbol{\gamma}$  and  $\sigma_\eta^2$

$$\begin{aligned} \mathcal{L}_{\text{con}}(\boldsymbol{\phi}, \lambda | \delta) = C - \frac{1}{2} \log \left| T \boldsymbol{\phi} \mathbf{I}_N + [\mathbf{A}'(\lambda) \mathbf{A}(\lambda)]^{-1} \right| + \\ \frac{T-1}{2} \log \left| \mathbf{A}'(\lambda) \mathbf{A}(\lambda) \right| - \frac{1}{2\sigma_\eta^2} \mathbf{e}'(\delta) \boldsymbol{\Sigma}_\varepsilon^{-1}(\boldsymbol{\phi}, \lambda) \mathbf{e}(\delta) \end{aligned} \quad (18)$$

where  $C$  is a constant term not depending on  $\boldsymbol{\phi}$ ,  $\lambda$  and  $\delta$ .

We follow an iterative procedure to obtain ML estimates for all parameters. This essentially alternates back and forth between the estimation of  $\boldsymbol{\phi}$  and  $\lambda$  conditional upon a vector of residuals  $\mathbf{e}$  (generated for a value of  $\hat{\boldsymbol{\gamma}}$  conditional upon  $\delta$ ) and an estimation of  $\boldsymbol{\gamma}$  (and  $\sigma_\eta^2$ ) conditional upon a value for  $\lambda$  and a value for  $\delta$ , until convergence is obtained. The estimator of  $\boldsymbol{\gamma}$ , given  $\lambda$ ,  $\boldsymbol{\phi}$  and  $\delta$ , is a generalized least squares (GLS) estimator. The estimates  $\boldsymbol{\phi}$ ,  $\lambda$  and  $\delta$  must be obtained by numerical methods because the equations cannot be solved analytically.

The main computational task in the iterative maximization process is the repeated evaluation of the log-determinants of the  $N$ -by- $N$  matrices  $\mathbf{A}'\mathbf{A}$  and  $T \boldsymbol{\phi} \mathbf{I}_N + [\mathbf{A}'\mathbf{A}]^{-1}$  afresh at each iteration step in the optimization process. Following Griffith (1988), the calculation of these determinants can be simplified by using

$$|\mathbf{A}(\lambda)| = \prod_{i=1}^N (1 - \lambda \omega_i) \quad (19)$$

$$\left| T \boldsymbol{\phi} \mathbf{I}_N + [\mathbf{A}'\mathbf{A}]^{-1} \right| = \prod_{i=1}^N \left[ T \boldsymbol{\phi} + (1 - \lambda \omega_i)^{-2} \right] \quad (20)$$

where  $\omega_i$  denotes the  $i$ th eigenvalue of  $\mathbf{W}$ . The only computational issue associated with this eigenvalue-route approach in panels with large cross-sectional dimensions involves the calculation of eigenvalues. Anselin (2001, pp. 325) pointed out that the computation of eigenvalues becomes instable when  $N$  is larger than 1,000, and much remains to be done to develop efficient algorithms and data structure to allow the analysis of very large panel data sets.

In this study we followed the eigenvalue route to computing the log-determinants and adopted Elhorst's software *respat* in combination with Brent's direct search procedure (see Press et al. 1992, pp. 402) to obtain the model parameters  $\gamma$ ,  $\sigma_{\eta}^2$ ,  $\phi$ ,  $\lambda$  and  $\delta$ .

## 5 Estimation results

The dependent variable is the relative productivity level as defined by Equation (4). The regressors are random region effects which are assumed to be *iid*  $(0, \sigma_{\eta}^2)$ , the region-internal knowledge stock and the out-of-region stock of knowledge defined as a spatially discounted sum of the internal knowledge stocks of all other regions as described by Equation (3).

The estimates are presented in Table 1 together with their standard errors, shown in parentheses. The first column reports the results given by the conventional random effects model (8)-(9). The estimation method is GLS. The productivity effect from region-internal knowledge is estimated as  $\gamma_1 = 0.194$ , with a standard error of 0.028. The parameter estimate of  $\gamma_2 = 0.138$  determines the relative potency of distance-deflated cross-region knowledge spillovers. The parameter estimate of  $\delta$  is equal to 0.073. This suggests that effective knowledge from external regions is falling exponentially with bilateral distance. The finding is consistent with the localization hypothesis. Productivity in regions that are far away from the spilling-out region is much lower than in those located closer, because knowledge diffusion and its productivity effects are geographically localized.

The second column presents the estimates of the random effects panel data spatial error model<sup>13</sup>. The  $\lambda$  estimate is 0.631, with a standard error of 0.040. A likelihood ratio test for the null hypothesis of  $\lambda = 0$  yields a  $\chi_1^2$  test statistic of 5,197.3. This is statistically significant and confirms the importance of a spatial autoregressive disturbance in the random effects model for measuring the TFP impact of cross-region knowledge spillovers. The TFP effects of internal and out-of-region stocks of knowledge are somewhat larger when the spatial autocorrelation due to neighbouring regions is taken explicitly into account. The strength of interregional knowledge spillovers is about five percent higher than in the specification that neglects the importance of a spatial autoregressive disturbance in the random effects model. At the same time the knowledge

localization effect becomes somewhat weaker. The distance decay (or localization) parameter  $\delta$  is estimated to be 0.056, with a standard error of 0.021.

### **Table 1 about here**

These results provide a fairly remarkable confirmation of the role of interregional knowledge spillovers as a statistically highly significant factor contributing to productivity differences among the regions. The  $\gamma_2$ -estimate implies that a one percent increase in the pool of out-of-region knowledge capital raises the average total factor productivity in the spill-in region by about 0.15 percent. The evidence based on the distance parameter, implicit in the construction of the pool of cross-region spillovers, indicates that the benefits from out-of-region knowledge capital are to a substantial degree decreasing with geographic distance. Formally integrating the spatial configuration of the data tends to slightly increase the TFP effects with respect to both the region's internal stock of knowledge and its pool of knowledge spillovers, by about five percent, while decreasing the distance decay effect by about 23 percent.

## **6 Concluding remarks**

The novelty of the new theory of economic growth essentially lies in explaining the growth of total factor productivity, which is the component of output growth not attributable to the accumulation of conventional input, such as labour and physical capital. This theory also underlines interregional economic relations that link a region's productivity gains to economic developments in other regions. For this reason, we have chosen to focus on the central link between productivity and knowledge capital at the regional level. The study departs from previous research not only by shifting attention from firms to regions, but also by adding an important dimension to the discussion, showing that knowledge spillover effects increase with geographic proximity.

Based on a regional Cobb-Douglas production function our evidence suggests that there indeed exist close links between productivity and knowledge capital. Not only does a region's total factor productivity depend on its own knowledge capital, but – as suggested by theory – it also depends on cross-region knowledge spillovers. While the beneficial effects on TFP from

interregional spillovers have been recently established in an US-American context (see Robbins 2006), the evidence of the importance of knowledge spillovers in Europe is new as is the incorporation of spatial autocorrelation due to neighbouring regions in order to avoid misleading inferences.

Our knowledge stock elasticity estimates suggest that the productivity effects are statistically significant and important, both in terms of region-internal stocks of knowledge and interregional knowledge spillovers. The evidence based on the distance decay parameter, implicit in the construction of the pool of cross-region spillovers, indicates that knowledge spillovers and their productivity effects are to a substantial degree geographically localized and this finding is consistent with the localization hypothesis.

The results are encouraging since they suggest that our search for interregional knowledge spillovers was not misplaced. Several suggestions for further research come to mind. First, further explorations with industry specific data and an explicit treatment of industry specific knowledge stocks and spillovers will undoubtedly provide new valuable insights. Second, on a methodological level, it would be of interest to extend the results of this paper to models containing spatially lagged dependent variables. In doing this, it would be certainly of interest to consider higher order spatial lags.

## Notes

- <sup>1</sup> See Mairesse and Sassenou 1991 for a survey of studies.
- <sup>2</sup> This literature generally relies on trade as the primary mechanism of knowledge diffusion, and hence on spillovers of the embodied kind.
- <sup>3</sup> Robbins (2006) and Smith (1999) are notable exceptions. Both provide empirical evidence on the contributions of inter-state spillovers within the United States. Smith (1999) applies international trade theory to subnational units, while Robbins (2006) has its roots in the technology diffusion literature of international trade.
- <sup>4</sup> An example is that the design of a new product may speed up the invention of a competing product, because the second inventor can learn from the first by carefully studying the product (Gong and Keller 2003).
- <sup>5</sup> Other recent works that have used this TFP index for other purposes includes Harrigan (1997), Keller (2002), and Robbins (2006).
- <sup>6</sup> Note that fractional counting gives the interregional cooperative inventions lower weight than full counting (see Fischer, Scherngell and Jansenberger 2006).
- <sup>7</sup> This depreciation rate corresponds to the rate of knowledge obsolescence in the United States over the past century, as found in Caballero and Jaffe (1993).
- <sup>8</sup> We group the data by time periods rather than cross-section units because this grouping is more convenient for modeling spatial autocorrelation via Equation (10).
- <sup>9</sup> Panel data models have been widely studied (see Baltagi 2001). Heterogeneity across cross-sectional units is generally modelled with an error component model.
- <sup>10</sup> The need to account for spatial heterogeneity is that regions are likely to differ in their background variables, that are generally region-specific time-invariant variables which affect the dependent variable, but are difficult to measure. Neglect of these variables leads to bias in the resulting estimates. One remedy is to introduce a variable intercept  $\mu_i$ , representing the effect of omitted variables which are specific to each region considered (Baltagi 2001). Conditional on the specification of  $\mu_i$ , model (8) can be estimated as a fixed or a random effects model. A Hausman (1978) test statistic for misspecification based on the difference between the fixed and random effects estimators of  $\gamma$  yields a  $\chi^2_2$  test statistic of 0.151, which is statistically insignificant ( $p = 0.928$ ). The null hypothesis is not rejected and we conclude that the random effects estimator is consistent.
- <sup>11</sup> This normalization has the advantage that the spatial weights matrix is kept symmetric (Elhorst 2005).
- <sup>12</sup> If  $\lambda = 0$ , so that there is no spatial autocorrelation, then  $A = I_N$  and  $\Omega_{\epsilon}$  from Equation (12) becomes the usual error component variance-covariance matrix  $\Omega_{\epsilon} = \sigma_{\mu}^2(\mathbf{1}_T \mathbf{1}'_T \otimes I_N) + \sigma_{\eta}^2(I_T \otimes I_N)$ .
- <sup>13</sup> We rely on jackknife estimates of the standard error for  $\delta$ ,  $\sigma_{\eta}^2$  and  $\sigma_{\mu}^2$ . They seem to be more reliable and, in any case, they are often much larger than standard error based on first-order asymptotics.



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## Appendix

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 statistical 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. The sample is composed of 203 NUTS-2 regions located in the pre-2004 EU member states (NUTS revision 1999, except for Finland NUTS revision 2003). We exclude the Spanish North African territories of Ceuta and Melilla, and the French Départments d'Outre-Mer Guadeloupe, Martinique, French Guayana and Réunion. Thus, we include the following NUTS 2 regions:

<i>Austria:</i>	Burgenland; Niederösterreich; Wien; Kärnten; Steiermark; Oberösterreich; Salzburg; Tirol; Vorarlberg
<i>Belgium:</i>	Région de Bruxelles-Capitale/Brussels Hoofdstedelijk Gewest; Prov. Antwerpen; Prov. Limburg (BE); Prov. Oost-Vlaanderen; Prov. Vlaams-Brabant; Prov. West-Vlaanderen; Prov. Brabant Wallon; Prov. Hainaut; Prov. Liége; Prov. Luxembourg (BE); Prov. Namur
<i>Denmark:</i>	Danmark
<i>Germany:</i>	Stuttgart; Karlsruhe; Freiburg; Tübingen; Oberbayern; Niederbayern; Oberpfalz; Oberfranken; Mittelfranken; Unterfranken; Schwaben; Berlin; Brandenburg; Bremen; Hamburg; Darmstadt; Gießen; Kassel; Mecklenburg-Vorpommern; Braunschweig; Hannover; Lüneburg; Weser-Ems; Düsseldorf; Köln; Münster; Detmold; Arnsberg; Koblenz; Trier; Rheinhessen-Pfalz; Saarland; Chemnitz; Dresden; Leipzig; Dessau; Halle; Magdeburg; Schleswig-Holstein; Thüringen
<i>Greece:</i>	Anatoliki Makedonia; Kentriki Makedonia; Dytiki Makedonia; Thessalia; Ipeiros; Ionia Nisia; Dytiki Ellada; Sterea Ellada; Peloponnisos; Attiki; Voreio Aigaio; Notio Aigaio; Kriti
<i>Finland:</i>	Itä-Suomi; Etelä-Suomi; Länsi-Suomi; Pohjois-Suomi
<i>France:</i>	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; Provence- Côte d'Azur; Corse
<i>Ireland:</i>	Border, Midland and Western, Southern and Eastern
<i>Italy:</i>	Piemonte; Valle d'Aosta; Liguria; Lombardia; Trentino-Alto Adige; Veneto; Friuli-Venezia Giulia; Emilia-Romagna; Toscana; Umbria; Marche; Lazio; Abruzzo; Molise; Campania; Puglia; Basilicata; Calabria; Sicilia; Sardegna
<i>Luxembourg:</i>	Luxembourg (Grand-Duché)
<i>Netherlands:</i>	Groningen; Friesland; Drenthe; Overijssel; Gelderland; Flevoland; Utrecht; Noord-Holland; Zuid-Holland; Zeeland; Noord-Brabant; Limburg (NL)
<i>Portugal:</i>	Norte; Centro (P); Lisboa e Vale do Tejo; Alentejo; Algarve; Açores; Madeira
<i>Spain:</i>	Galicia; Asturias; Cantabria; Pais Vasco; Comunidad Foral de Navar; La Rioja; Aragón; Comunidad de Madrid; Castilla y León; Castilla-la Mancha; Extremadura; Cataluña; Comunidad Valenciana; Islas Baleares; Andalucia; Región de Murcia
<i>Sweden:</i>	Stockholm; Östra Mellansverige; Sydsverige; Norra Mellansverige; Mellersta Norrland; Övre Norrland; Småland med öarna; Västsverige
<i>United Kingdom:</i>	Tees Valley & Durham; Northumberland & Wear; Cumbria; Cheshire; Greater Manchester; Lancashire; Merseyside; East Riding & .Lincolnshire; North Yorkshire; South Yorkshire; West Yorkshire; Derbyshire & Nottingham; Leicestershire; Lincolnshire; Herefordshire; Shropshire & Staffordshire; West Midlands; East Anglia; Bedfordshire & Hertfordshire; Essex; Inner London; Outer London; Berkshire; Surrey; Hampshire & Isle of Wight; Kent; Gloucestershire; Dorset & Somerset; Cornwall & Isles of Scilly; Devon; West Wales; East Wales; North Eastern Scotland; Eastern Scotland; South Western Scotland; Highlands and Islands; Northern Ireland

**Table 1** Total factor productivity estimation results (pooled data 1997-2002;  $N = 203$ ,  $T = 6$ )

	The conventional random effects model [GLS]	The random effects model with spatially autocorrelated errors [ML]
Parameters (standard errors in parentheses)		
The region-internal stock of knowledge [ $\gamma_1$ ]	0.194** (0.028)	0.203** (0.028)
Interregional knowledge spillovers [ $\gamma_2$ ]	0.138** (0.030)	0.145** (0.029)
The distance decay parameter [ $\delta$ ]	0.073* (0.025)	0.056* (0.021)
The spatial autocorrelation coefficient [ $\lambda$ ]	—	0.631** (0.040)
Variance $\sigma_{\eta}^2$	0.004** (0.001)	0.004** (0.000)
Variance $\sigma_{\mu}^2$	0.172** (0.024)	0.155** (0.009)
Likelihood ratio test statistic	—	5,197.314 (0.000)
<i>AIC</i>	-2,016.853	-2,206.147
Number of observations	1,218	1,218

*Notes:* The dependent variable is the multilateral TFP index, as defined in the text. Standard errors are in parentheses.  $\gamma_1$  measures the effect of region-internal stocks of knowledge; and  $\gamma_2$  determines the strength of the cross-region knowledge spillover effects on productivity;  $\delta$ , implicit in the construction of out-of-region knowledge capital  $k^*$ , determines the distance effects; *AIC* is Akaike's Information Criterion (a lower *AIC* value is preferred), \*\* denotes significance at the 0.001 significance level, \*significance at the 0.05 significance level.