Knowledge spillovers and total factor productivity. Evidence using a spatial panel data model

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Abstract. This paper investigates the impact of knowledge capital stocks on total factor productivity through the lens of the knowledge capital model proposed by Griliches (1979), augmented with a spatially discounted cross-region knowledge spillover pool variable. The objective is to shift attention from firms and industries to regions and to estimate the impact of cross-region knowledge spillovers on total factor productivity (TFP) in Europe. The dependent variable is the region-level TFP, measured in terms of the superlative TFP index suggested by Caves, Christensen and Diewert (1982). This index describes how efficiently each region transforms physical capital and labour into output. The explanatory variables are internal and out-of-region stocks of knowledge, the latter capturing the contribution of cross-region knowledge spillovers. We construct patent stocks to proxy regional knowledge capital stocks for N=203 regions over the 1997-2002 time period. In estimating the effects we implement a spatial panel data model that controls for the spatial autocorrelation due to neighbouring regions and the individual heterogeneity across regions. The findings provide a fairly remarkable confirmation of the role of knowledge capital contributing to productivity differences among regions, and add an important spatial dimension to the discussion, by showing that productivity effects of knowledge spillovers increase with geographic proximity.

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

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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 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), defined as output per unit labour and physical capital combined.

This paper lies in the research tradition that investigates the impact of knowledge capital stocks on total factor productivity through the lens of the knowledge capital model proposed by Griliches (1979) to augment the production function with the stock of knowledge[1]. The knowledge capital model has become the cornerstone of the productivity literature for more than 25 years and has been applied in dozens of empirical studies on firm-level productivity and extended to the more aggregated industry- and country-levels (see Griliches 1995 for a survey).

This model has evolved in many directions. Jaffe (1986) initiated ways of accounting for the appropriability of external flows of knowledge or knowledge spillovers. Knowledge spillovers may be defined to denote the benefits of knowledge to firms, industries or regions not responsible for the original investment in the creation of this knowledge. It is important to distinguish between two distinct types of knowledge spillovers: Spillovers embodied in traded capital or intermediate goods and services (so-called pecuniary externalities)[2] and spillovers of the disembodied kind (non-pecuniary externalities). The focus of this paper is on spillovers of the second type. Such spillovers arise because the production of knowledge has public good characteristics limiting the ability of firms to stop other firms or individuals exploring it.

[1] It is worth emphasizing that this field is rather different from the abundance of studies that aim to estimate a knowledge production function that relates the output of the knowledge production process, the increment of economically valuable technological knowledge in a region, to R&D inputs. Regional knowledge production is seen to depend on two major sources: university research and commercial R&D (see, for example, Anselin, Varga and Acs 1997; Fischer and Varga 2003). Such knowledge production function studies allow for testing hypotheses about the impact of spillovers from academic research and about the existence of Jacobian spillovers, and permit statements about the spatial extent of knowledge externalities but no statements about productivity effects.

[2] As pointed out by Griliches (1995), pecuniary externalities that work through the price system are not really a case of pure spillovers. They are often just consequences of conventional measurement problems.

The last few years have seen the development of a significant body of research that includes measures of external knowledge capital in an attempt to estimate the productivity effects of knowledge spillovers across firms (see, for example, Los and Verspagen 2000, and Mairesse and Sassenou 1991 for a survey), across industries (see, for example, Scherer 1993, and Branstetter 2001) or across countries (see, for example, Park 1995)[3]. Even though the subnational region is increasingly regarded as an important level of economic policy, there have been very few attempts so far to investigate the impact of knowledge capital stocks on region-level total factor productivity. One notable exception is the study by Robbins (2006) which finds mixed evidence in terms of the significance of industry-specific knowledge spillovers at the state level in the US, and a lack of evidence in most manufacturing industries. This contradicts the strong findings in firm-level, sectoral and country-level studies.

The objective of our study is to investigate whether knowledge spilling across regional boundaries has an impact on regional total factor productivity in manufacturing industries 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 spillover 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).

[3] It is worth noting that Coe and Helpman (1995) use weights related to input purchase flows to measure the impact of international knowledge spillovers. But these are pecuniary rather than non-pecuniary externalities.

In using patent stocks[4] to proxy knowledge stocks, we build on Robbins (2006), but depart from this previous work at least in two major aspects. *First*, we extend the knowledge capital model with a spatially discounted cross-region knowledge spillover pool variable that allows to measure rather than to assume the degree of localization of such spillovers, and *second*, we account for spatial error autocorrelation due to neighbouring regions and the individual heterogeneity across regions in estimating the model and, hence, avoid misspecification problems.

The remainder of this paper is organized as follows. The section that follows presents the reduced-form model that relates regional TFP not only to region-internal knowledge capital but also to cross-region knowledge spillovers. We use a region-level relative TFP index – suggested by Caves, Christensen and Diewert (1982) – as an approximation to the true TFP measure and patent stocks to proxy regional knowledge capital stocks. Section 3 details the definition of the TFP index and the construction of the regional patent stocks. Important econometric issues raised by the estimation of the model are addressed in Section 4, while Section 5 reports the estimation results. Section 6 concludes the paper.

2 The empirical model

The model used in this paper builds on the knowledge capital model (see Griliches 1979, Doraszerlski and Jaumandreu 2008), but modifies it so that the region's total factor productivity depends not only on its own knowledge capital stock, but also on the level of the pool of general knowledge accessible to it. Denote regions by $i = 1,...,N$ and time periods by $t = 1,...,T$. Ignoring constants, time trends or year dummies, the regional production function is given by

[4] An alternative, widely used in firm-level studies, would be to use measures of R&D input. One problem with this way to proxy knowledge spillovers is that some double counting occurs because R&D labour and capital are counted twice, once in the available measures of labour and physical capital, and again in the measure of R&D capital stocks (see, for example, the study by Griliches and Mairesse 1984). As the necessary data are generally not available, double counting cannot be corrected for. Using patents, we avoid this problem as well as the problem of potential endogeneity of the knowledge spillover stock variable. But patents have their own weaknesses. This measure is most flawed by the fact that not all important inventions have been patented, while many patents represent only incremental inventions.

$$Q_{it} = A_{it} \; g(L_{it}, C_{it}) \tag{1}$$

where $g(.,.)$ is assumed to be homogeneous of degree one and to exhibit diminishing marginal returns to the accumulation of each factor alone. *C* is the stock of physical capital, *L* the stock of labour, *Q* value added, and *A* an index of the technical efficiency of production with

$$A_{it} = A(K_{it}, K_{it}^{*}) \tag{2}$$

where K and K^{*} are the stocks of region-internal and region-external knowledge capital, respectively. The stocks of knowledge capital are proxies for the state of knowledge. The knowledge created by a private or public agent is added to the pool of the existing knowledge capital stock to which other agents have access. Note that even if the benefits of R&D activities are fully appropriated by an agent, in the sense that an agent acquires a monopoly right by patent protection, some portion of the knowledge that has led to the patent may diffuse across regions through various communication channels such as publications, seminars, personal contacts, reverse engineering, (informal) exchange in networks, transfer of human capital and other means (Park 1995).

In an *N*-region world, the *global* stock of knowledge capital is given by

$$\sum_{j=1}^{N} K_{jt} \tag{3}$$

where the subscript *j* denotes the *j*th region, and knowledge capital K_{jt} is assumed to accumulate with knowledge production activities and to depreciate from period to period at a rate r_K. Hence, its law of motion can be written as

$$K_{jt} = (1 - r_K) \; K_{jt-1} + S_{jt-1} = K_{jt-1} \left(1 - r_K + \frac{S_{jt-1}}{K_{jt-1}} \right) \tag{4}$$

This law implies that knowledge production activities S_{jt-1} undertaken in period t–1 become productive in period t.

For region i, K_{it} represents its own knowledge capital stock in period t and K^*_{it} its relevant pool of knowledge spillovers. Since not all knowledge capital will necessarily spill over from one region to another, it seems appropriate to define K^*_{it} as[5]

$$K^*_{it} = \sum_{j \neq i}^{N} w_{ij}\, K_{jt-m} \tag{5}$$

where w_{ij} represents region's i ability to internalize pieces of region's j knowledge stock for production in region i, and K_{jt-m} represents the knowledge capital stock of region j at time t–m (m positive integer).

The term $w_{ij}\, K_{jt-m}$ may be interpreted as the effective fraction (pool) of the stock of knowledge in region j "borrowed" by region i. The time lag is important since it takes time for knowledge spillovers from region j to be expressed in new products and processes in region i. We construct a spatially discounted time-lagged pool by assuming that the effective knowledge contribution by each of the regions j $(j \neq i)$ depends on the geographic distance between that region j and region i. This is quite in line with the literature on spatial knowledge spillovers (see Döring and Schellenbach 2006 for a survey). Empirical work by Jaffe, Trajtenberg and Henderson (1993), for example, on patent citations proxying knowledge spillovers showed the spatial decay in knowledge spillovers relative to the patent source, which was interpreted as knowledge diffusion decay. This motivated us to follow Fischer, Scherngell and Jansenberger (2006) in assuming a parametric exponential dependence between weights and geographic distance as given by[6]

[5] The definition shows that one faces two major problems in constructing the relevant pool of knowledge spillovers, deciding on the appropriate time lag structure m and finding an appropriate weight structure $\{w_{ij}, i \neq j\}$ to represent borrowed knowledge and spillovers.

[6] This exponential specification is attractive because of its theoretical underpinning in spatial interaction theory and analysis (see Fischer and Reggiani 2004). In addition, it shows some nice properties. It is symmetric so that

$$w_{ij} = \exp(-\delta\, d_{ij}) \qquad (6)$$

which enables us to test rather than to assume the strength of the spatial dependence. d_{ij} denotes geographic distance, in some sense, between the knowledge spilling region *j* and the knowledge receiving region *i*. δ is the distance sensitivity parameter that captures the impact of distance on the spillover variable. Estimating $\delta = 0$ would mean that distance would not matter. Positive δ-estimates would suggest that the benefits from out-of-region knowledge capital stocks exponentially decline with distance. Different distance measures can be used to represent possible geographic impediments to the free flow of knowledge across space. In the context of our study we measure distance between regions *i* and *j* as great circle distance between their economic centres[7].

Substituting Equation (2) into Equation (1) and assuming a Cobb-Douglas production technology gives, for region *i*,

$$Q_{it} = Q(K_{it}, K^*_{it}, L_{it}, C_{it}) = K_{it}^{\gamma_1}\; K_{it}^{*\gamma_2}\; L_{it}^{\alpha}\; C_{it}^{1-\alpha}\; \exp(\varepsilon_{it}) \qquad (7)$$

where α, $1-\alpha$, γ_1, γ_2 are the output elasticities with respect to labour, physical capital, region-internal and region-external knowledge capital. ε is the error term reflecting all unmeasured determinants of output and productivity, approximations and other disturbances.

Define total factor productivity *F* in the usual way as $F_{it} = Q_{it} / (L_{it}^{\alpha}\; C_{it}^{1-\alpha})$ then it is easy to see how total factor productivity is linked to knowledge stocks inside and outside the region in question:

$\exp(-\delta\, d_{ij})$ equals $\exp(-\delta\, d_{ji})$. When d_{ij} equals zero, $\exp(-\delta d_{ij})$ equals one. As d_{ij} approaches infinity, $\exp(-\delta\, d_{ij})$ approaches zero.

[7] Travel distance is an alternative measure (see, for example, Crescenzi, Rodríguez-Pose and Storper 2007, LeSage and Fischer 2007), that is especially attractive in contexts where knowledge diffusion primarily takes place with face-to-face interaction.

$$f_{it} = \gamma_1\, k_{it} + \gamma_2\, k^*_{it} + \varepsilon_{it} = \gamma_1\, k_{it} + \gamma_2\, \log\left[\sum_{j\neq i}^{N} \exp(-\delta\, d_{ij})\, K_{jt-m}\right] + \varepsilon_{it} \tag{8}$$

where we follow the convention that lower case letters denote logs and upper case letters levels, that is $f_{it} = \log F_{it}$, $k_{it} = \log K_{it}$ and $k^*_{it} = \log K^*_{it}$. Equation (8) is a simple panel data regression model, where *i* denotes the cross-section and *t* the time series dimension. γ_1 measures the effect of the region's own knowledge capital stock on total factor productivity, while γ_2 captures the relative effect from cross-region knowledge spillovers. A positive and significant estimate of γ_2 is interpreted as evidence of such spillovers. For $\delta > 0$, variation in regional productivity levels is best accounted for by giving a lower weight to knowledge capital stocks in regions *j* that are located relatively far away from region *i*. If $\delta = 0$, then geographic distance and relative location do not matter. Note that γ_1, γ_2 and δ have to be estimated. There is no agreement on the correct length of the time lag. Since the data we have are not rich enough in the time dimension to determine the lag structure *m* in the knowledge spillover-productivity nexus, the assumption is made that knowledge spillovers take one year to affect productivity.

Model specification (8) can be thought of as a multi-region extension of the knowledge capital model that relates region-level TFP to only region-internal knowledge capital, which would be a special case with $\gamma_2 = 0.$ Of course, this skeletal regression model is rather simplistic and based upon a whole string of untenable assumptions, the major ones being a Cobb-Douglas production technology with constant returns to scale with respect to physical capital and labour. One can raise immediately a number of reservations about this model. There are major difficulties in the specification and measurement of the dependent variable, and there are issues of timing, depreciation and coverage in the construction of the regional knowledge stock variables. Nevertheless, this simple model allows analysing the reduced-form relationship between knowledge capital and productivity, and provides useful information on this long-run average relationship at the regional level. In this reduced form, γ_1 and γ_2 are the elasticities of TFP with respect to region-internal and out-of-region knowledge capital.

3 Data and variables

Our empirical results are based on data for N=203 regions over the 1997-2002 period. 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. The observation units are NUTS-2 regions that are adopted by the European Commission for the 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 NUTS-2 regions located in the 15 pre-2004 EU member states. The Appendix describes the sample of regions.

Empirical implementation of the model described in the previous section requires data on total factor productivity[8] and knowledge stocks for each of the N regions at six points in time. TFP calculations at the regional level require interregionally comparable data on regional outputs and inputs such as physical capital and labour. Since regional TFP comparisons are a classic index number problem, we use a TFP index to register the impact of knowledge capital stocks. Unfortunately, TFP indices have no unique optimal form. In line with Harrigan (1997), Keller (2002) and Robbins (2006) we have chosen the index proposed by Caves, Christensen and Diewert (1982). This choice is well justified. *First*, the index is *superlative*, meaning that it is an approximation if the production function takes the general neoclassical form, but holds exactly for the flexible translog functional form. *Second*, the index meets the *circularity test* which is often referred to as transitivity. This makes the choice of the base region and year inconsequential. *Third*, superlative index numbers that maintain circularity can be used for making multilateral comparisons, not only for cross-section and time series comparisons, but also for combinations of both. Formally, the index is defined by

[8] Interested readers for a review of different approaches to the theory and measurement of TFP are referred to Nadiri (1970) and Diewert (1992).

$$f_{it} = (q_{it} - \overline{q}_t) - s_{it}(l_{it} - \overline{l}_t) - (1 - s_{it})(c_{it} - \overline{c}_t) \tag{9}$$

where f_{it} is the log of total factor productivity of region *i* at time *t*, q_{it} the log of output, l_{it} the log of labour, c_{it} the log of physical capital, and s_{it} is the share of labour in total production costs. An upper bar above a variable denotes a geometric mean.

Note that 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 output. 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 investment in current prices is. Thus, we constructed the stocks of physical capital for each region by using the perpetual inventory method $C_{it} = (1 - r_C)\, C_{it-1} + I_{it-1}$, where C_{it} is the stock of physical capital of region *i* at time *t*, I_{it-1} is the flow of gross investment in period *t*–1, becoming productive in period t, and r_C is the constant depreciation rate. We applied a constant rate of ten percent depreciation across space and time. The annual flows of fixed investments were deflated by national gross fixed capital formation deflators. The mean annual rate of growth, which precedes the benchmark year 1997, covers the period 1990-1997 to estimate initial regional capital stocks.

Besides the TFP measure, Equation (8) contains also a measure of the knowledge capital stock for each of the N regions and the six time periods. We use patent applications to proxy knowledge capital. 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).

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 1990-2002 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 inventor resides. In the case of cross-region inventor teams we used the procedure of fractional rather than full counting. Then for each region, the annual patents were aggregated using Equation (4), with a constant depreciation rate[9] $r_K = 12$ percent applied for each year to the stock of patents created in earlier years. Thus, the region-internal knowledge stocks, K_{it} $(i = 1,..., N;\ t = 1,...,T)$, may be viewed as depreciated sums over time of patents applied by inventors in region *i*, while the out-of-region knowledge stocks, K_{it}^* $(i = 1,..., N;\ t = 1,...,T)$, are spatially discounted sums over time of the time-lagged internal knowledge stocks of all regions *j* excluding *i*.

4 Error specification and model estimation

In estimating Equation (8), the disturbance vector is assumed to have random region effects as well as spatially autocorrelated residual disturbances[10, 11]

$$\boldsymbol{\varepsilon}_t = \boldsymbol{\mu} + \boldsymbol{\zeta}_t \tag{10}$$

with

$$\boldsymbol{\zeta}_t = \lambda \boldsymbol{W} \boldsymbol{\zeta}_t + \boldsymbol{\eta}_t \tag{11}$$

where $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t},...,\varepsilon_{Nt})'$, $\boldsymbol{\zeta}_t = (\zeta_{1t},...,\zeta_{Nt})'$, and $\boldsymbol{\mu} = (\mu_1,...,\mu_N)'$ denotes the vector of random region effects which are assumed to be *iid* (0, σ_μ^2). $\boldsymbol{\eta}_t = (\eta_{1t},...,\eta_{Nt})'$ where η_{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 $\{\mu_i\}$. λ is the scalar spatial autoregressive coefficient with $|\lambda| < 1$. $\boldsymbol{W}$ is a known *N*-by-*N* spatial weights matrix where diagonal elements are zero. In this study, the weights matrix is constructed so that

9 We used a constant rate of obsolescence because of evident complications in tracking obsolescence over time. The depreciation rate $r_K = 12$ percent corresponds to the rate of knowledge obsolescence in the US over the past century, as found in Caballero and Jaffe (1993).

10 This error component specification corresponds to that suggested by Anselin (1988, pp. 152). But note that our spatial panel data model differs from his model somewhat in that we allow one independent variable, the knowledge spillover pool variable, to depend on a spatial deterrence function with an a priori unknown δ-parameter. The inclusion of this parameter in the specification of the pool of cross-region spillovers complicates maximum likelihood (ML) model estimation.

11 One of the referees suggests to use an alternative and more general error component specification developed by Kapoor, Kelejian and Prucha (2007) for GM-based spatial panel data models. The authors show the GMM coefficient estimates to be consistent, but the inferential statistics for these parameters appear to be ad-hoc at best.

a neighbouring region takes the value of one and zero otherwise. The rows of this matrix are normalized[12] by the largest characteristic root of $\boldsymbol{W}$. Thus, the matrix $(\boldsymbol{I}_N - \lambda \boldsymbol{W})$ is non-singular, where $\boldsymbol{I}_N$ 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.

One can rewrite (11) as

$$\boldsymbol{\xi}_t = (\boldsymbol{I}_N - \lambda \boldsymbol{W})^{-1} \boldsymbol{\xi}_t = \boldsymbol{A}^{-1} \boldsymbol{\eta}_t \tag{12}$$

where $\boldsymbol{A} = \boldsymbol{I}_N - \lambda \boldsymbol{W}$, and $\boldsymbol{I}_N$ is an identity matrix of dimension N. Model (8) can be rewritten in matrix notation as

$$\boldsymbol{f} = \boldsymbol{X} \boldsymbol{\gamma} + \boldsymbol{\varepsilon} \tag{13}$$

where $\boldsymbol{f}$ is of dimension NT-by-1, $\boldsymbol{X}$ is NT-by-2, $\boldsymbol{\gamma}$ is 2-by-1 and $\boldsymbol{\varepsilon}$ is NT-by-1. The observations are ordered by t being the slow running index and i is the fast running index[13], i.e., $\boldsymbol{f} = (f_{11}, \ldots, f_{N1}, \ldots, f_{1T}, \ldots, f_{NT})'$.

Equation (10) can be written in vector form as

$$\boldsymbol{\varepsilon} = (\boldsymbol{\iota}_T \otimes \boldsymbol{I}_N) \boldsymbol{\mu} + (\boldsymbol{I}_T \otimes \boldsymbol{A}^{-1}) \boldsymbol{\eta} \tag{14}$$

where $\otimes$ denotes the Kronecker product, $\boldsymbol{\iota}_T$ is a vector of ones of dimension T, and $\boldsymbol{I}_T$ is an identity matrices of dimension T.

Under these assumptions, the variance-covariance matrix for $\boldsymbol{\varepsilon}$ is

[12] This normalization has the advantage that the spatial weights matrix is kept symmetric (Elhorst 2005).

[13] We group the data by time periods rather than cross-section units because this grouping is more convenient for modelling spatial autocorrelation via Equation (11).

$$\boldsymbol{\Omega}_{\varepsilon} = E[\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}'] = E[\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}'] = \sigma_{\mu}^{2}(\boldsymbol{J}_T \otimes \boldsymbol{I}_N) + \sigma_{\eta}^{2}\left[\boldsymbol{I}_T \otimes (\boldsymbol{A}'\boldsymbol{A})^{-1}\right] \tag{15}$$

where $\boldsymbol{J}_T$ is a matrix of ones of dimension *T*, and $\boldsymbol{J}_T = \boldsymbol{\iota}_T \boldsymbol{\iota}'_T$. Following Baltagi, Song and Koh (2003), this variance-covariance matrix can be rewritten in such a way that[14]

$$\boldsymbol{\Omega}_{\varepsilon} = \sigma_{\eta}^{2}\left\{\bar{\boldsymbol{J}}_T \otimes \left[T\,\phi\,\boldsymbol{I}_N + (\boldsymbol{A}'\boldsymbol{A})^{-1}\right] + \boldsymbol{E}_T \otimes (\boldsymbol{A}'\boldsymbol{A})^{-1}\right\} = \sigma_{\eta}^{2}\,\boldsymbol{\Sigma}_{\varepsilon} \tag{16}$$

where $\phi = \sigma_{\mu}^{2}/\sigma_{\eta}^{2}$, $\bar{\boldsymbol{J}}_T = \boldsymbol{J}_T / T$, $\boldsymbol{E}_T = \boldsymbol{I}_T - \bar{\boldsymbol{J}}_T$, and $\boldsymbol{\Sigma}_{\varepsilon} = \left\{\bar{\boldsymbol{J}}_T \otimes \left[T\,\phi\,\boldsymbol{I}_N + (\boldsymbol{A}'\boldsymbol{A})^{-1}\right] + \boldsymbol{E}_T \otimes (\boldsymbol{A}'\boldsymbol{A})^{-1}\right\}$. Following Wansbeek and Kapteyn (1983), $\boldsymbol{\Sigma}_{\varepsilon}^{-1}$ is given by

$$\boldsymbol{\Sigma}_{\varepsilon}^{-1} = \bar{\boldsymbol{J}}_T \otimes \left[T\,\phi\,\boldsymbol{I}_N + (\boldsymbol{A}'\boldsymbol{A})^{-1}\right]^{-1} + \boldsymbol{E}_T \otimes (\boldsymbol{A}'\boldsymbol{A}) \tag{17}$$

which involves no matrix inversions of dimension larger than *N*. Also, $\left|\boldsymbol{\Sigma}_{\varepsilon}\right| = \left|T\,\phi\,\boldsymbol{I}_N + (\boldsymbol{A}'\boldsymbol{A})^{-1}\right| \left|(\boldsymbol{A}'\boldsymbol{A})^{-1}\right|^{T-1}$.

Under the assumption of normality, the log-likelihood for our model, conditional on δ, becomes (see Anselin 1988, pp. 154, Baltagi, Song and Koh 2003) as

$$\begin{aligned}\mathcal{L}(\gamma,\sigma_{\eta}^{2},\phi,\lambda \mid \delta) &= -\tfrac{NT}{2}\ln(2\pi\,\sigma_{\eta}^{2}) - \tfrac{1}{2}\ln\left|\boldsymbol{\Sigma}_{\varepsilon}\right| - \tfrac{1}{2\sigma_{\eta}^{2}}\boldsymbol{e}'\boldsymbol{\Sigma}_{\varepsilon}^{-1}\boldsymbol{e} = \\ &= \tfrac{NT}{2}\ln(2\pi\,\sigma_{\eta}^{2}) - \tfrac{1}{2}\ln\left|T\,\phi\,\boldsymbol{I}_N + (\boldsymbol{A}'\boldsymbol{A})^{-1}\right| + \tfrac{T-1}{2}\ln\left|\boldsymbol{A}'\boldsymbol{A}\right| - \tfrac{1}{2\sigma_{\eta}^{2}}\boldsymbol{e}'\boldsymbol{\Sigma}_{\varepsilon}^{-1}\boldsymbol{e}\end{aligned} \tag{18}$$

where $\boldsymbol{e} = (e_1,\dots,e_T)'$ and $e_t = (\boldsymbol{f}_t - \boldsymbol{X}_t\,\gamma)$. First order conditions for the ML estimates and the elements of the information matrix can be obtained in the usual way (see Anselin 1988, p. 154, and Elhorst 2003, p. 253).

[14] If λ = 0, so that there is no spatial autocorrelation, then $\boldsymbol{A} = \boldsymbol{I}_N$ and $\boldsymbol{\Omega}_{\varepsilon}$ from Equation (16) becomes the usual error component variance-covariance matrix $\boldsymbol{\Omega}_{\varepsilon} = \sigma_{\mu}^{2}(\boldsymbol{J}_T \otimes \boldsymbol{I}_N) + \sigma_{\eta}^{2}(\boldsymbol{I}_T \otimes \boldsymbol{I}_N)$.

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

$$|\boldsymbol{A}(\lambda)| = \prod_{i=1}^{N} (1-\lambda\,\omega_i) \tag{19}$$

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

where ω_i denotes the ith eigenvalue of $\boldsymbol{W}$. The only computational issue associated with this eigenvalue-route approach in panels with large cross-sectional dimensions involves the calculation of eigenvalues[15]. 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 γ, σ_η^2, ϕ, λ and δ.

5 Estimation results

The dependent variable is region-level TFP as defined by Equation (9). The regressors are random region effects which are assumed to be *iid* $(0, \sigma_\eta^2)$, the region-internal knowledge capital stock and the knowledge spillover pool variable defined as a spatially discounted sum of the time-lagged internal knowledge stocks of all other regions as described by Equations (5)-(6).

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 panel data model (10)-(11). The estimation method is GLS. The productivity effect from region-internal

[15] Anselin (2001, pp. 325) pointed out that the computation of eigenvalues becomes instable when N is larger than 1,000 observations, and much remains to be done to develop efficient algorithms and data structures to allow the analysis of very large panel data sets.

knowledge is estimated as $\gamma_1 = 0.200,$ with a standard error of 0.026. The parameter estimate of $\gamma_2 = 0.120$ determines the relative potency of distance-deflated cross-region knowledge spillovers. The parameter estimate of δ is equal to 0.080. This suggests that effective knowledge from external regions is falling exponentially with bilateral distance. Productivity effects 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 spatial panel data model. The λ estimate is 0.640, with a standard error of 0.040. A likelihood ratio test for the null hypothesis of $\lambda = 0$ yields a χ_1^2 test statistic of 5,197.314. 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 spatial autocorrelation due to neighbouring regions is taken explicitly into account. The strength of interregional knowledge spillovers is about 4.7 percent higher than in the specification that neglects the importance of a spatial autoregressive disturbance in the random effects model. The distance decay (or localization) parameter δ is estimated to be 0.072, with a standard error of 0.027. This is consistent with the hypothesis of geographic localization of interregional knowledge spillovers, and supports Bottazzi and Peri's (2003) findings on innovation and spillovers in European regions that a significant positive impact of knowledge spillovers on innovative activities in neighbouring regions appears to exist only for a distance up to 300 km.

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 γ_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 0.13 percent. This confirms that cross-region knowledge spillovers reinforce the impact of the region-internal knowledge stock, and – to a certain extent – may even compensate for a weaker contribution of the region's own knowledge stock. The evidence based on the distance parameter, inherent 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 4.5 percent, while decreasing the distance decay effect by about 10 percent.

6 Closing comments

Although regional studies of economic growth and convergence have been recently in abundance, they characteristically focus on explaining output growth, as determined by the accumulation of physical capital, labour and some additional socioeconomic variables. 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 cross-regional knowledge spillovers at the regional level. The issue is not so much a question whether or not such a relationship exists. Firm-level productivity studies and other factual knowledge in the field leave little doubt on this. The question, however, is whether or not econometric studies can characterize such a relationship in a satisfactory manner at the regional level of observation.

In spite of all the measurement difficulties and reservations with our simple reduced-form model, derived from the knowledge capital model, the work presented in this paper has yielded a number of interesting results. First and foremost, our evidence suggests that a region's total factor productivity depends not only on its own knowledge capital stock, but also – as suggested by the theory – on the stocks of knowledge capital of its neighbouring regions. While the beneficial effects on TFP from region-internal knowledge have been established in earlier studies, the evidence of the importance of external knowledge capital is new. The second main result is that knowledge spillovers and their productivity effects are to a substantial degree geographically localized, and this finding is consistent with the localization hypothesis, and supports, at the regional level, the cross-country findings of Keller (2002).

The final conclusion is about the research agenda for the future. All the computations described above capture only those contributions of knowledge that are measured at the aggregate regional level. Our current understanding may be improved by looking at industry-specific data and considering explicitly industry-specific knowledge capital stocks and spillovers. Another avenue for future research is to extend our framework to allow not only for geographical, but also for technological dependence between regions. This would permit us to quantify knowledge spillover effects arising from both spatial and technological proximity.

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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 Départements d'Outre-Mer Guadeloupe, Martinique, French Guayana and Réunion. Thus, we include the following NUTS 2 regions:

Austria:	Burgenland; Niederösterreich; Wien; Kärnten; Steiermark; Oberösterreich; Salzburg; Tirol; Vorarlberg
Belgium:	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
Denmark:	Danmark
Germany:	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
Greece:	Anatoliki Makedonia; Kentriki Makedonia; Dytiki Makedonia; Thessalia; Ipeiros; Ionia Nisia; Dytiki Ellada; Sterea Ellada; Peloponnisos; Attiki; Voreio Aigaio; Notio Aigaio; Kriti
Finland:	Itä-Suomi; Etelä-Suomi; Länsi-Suomi; Pohjois-Suomi
France:	Île de France; Champagne-Ardenne; Picardie Haute-Normandie; Centre; Basse-Normandie; Bourgogne; Nord-Pas-de-Calais; Lorraine; Alsace; Franche-Comté; Pays de la Loire; Bretagne;

	Poitou-Charentes; Aquitaine; Midi-Pyrénées; Limousin; Rhône-Alpes; Auvergne; Languedoc-Roussillon; Provence-Côte d'Azur; Corse
Ireland:	Border, Midland and Western; Southern and Eastern
Italy:	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
Luxembourg:	Luxembourg (Grand-Duché)
Netherlands:	Groningen; Friesland; Drenthe; Overijssel; Gelderland; Flevoland; Utrecht; Noord-Holland; Zuid-Holland; Zeeland; Noord-Brabant; Limburg (NL)
Portugal:	Norte; Centro (P); Lisboa e Vale do Tejo; Alentejo; Algarve; Açores; Madeira
Spain:	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
Sweden:	Stockholm; Östra Mellansverige; Sydsverige; Norra Mellansverige; Mellersta Norrland; Övre Norrland; Småland med Öarna; Västsverige
United Kingdom:	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 spatial panel data model [ML]
Region-internal stock of knowledge capital [γ_1]	0.200^{**} (0.026)[1]	0.209^{**} (0.026)[1]
Interregional knowledge spillovers [γ_2]	0.120^{**} (0.021)[1]	0.126^{**} (0.020)[1]
Distance sensitivity parameter [δ]	0.080^{*} (0.036)[1,2]	0.072^{*} (0,027)[1,2]
Spatial autocorrelation coefficient [λ]	—	0.640^{**} (0.040)[1]
Variance σ_{η}^{2}	0.004^{**} (0.000)[1,2]	0.004^{**} (0.000)[1,2]
Variance σ_{μ}^{2}	0.173^{**} (0.024)[1,2]	0.155^{**} (0.009)[1,2]
Likelihood ratio test statistic (p-value)	—	5,197.314 (0.000)
Log likelihood	-1,016.363	-1,114.629
AIC	-2,026.726	-2,223.258

** denotes significance at the 0.001 level; and * significance at the 0.05 level;

[1] standard errors in brackets;

[2] standard errors based on jackknife estimates [they seem to be more reliable and – in any case – often much larger than standard error based on first-order asymptotics].