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Total factor productivity effects of interregional knowledge spillovers in manufacturing industries across Europe

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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.

Martin Reismann (1973) is IT manager at the Institute for Economic Geography and GIScience of the Vienna University of Economics and Business Administration. He received his M.A. degree in 1999 from the University of Vienna. His research interests focus on GeoComputation in general and on neural spatial interaction modelling in particular

Abstract. The objective of this study is to identify knowledge spillovers that spread across regions in Europe and vary in magnitude for different industries. The study uses a panel of 203 NUTS-2 regions covering the 15 pre-2004 EU-member-states to estimate the impact over the period 1998-2003, and distinguish between five major industries. The study implements a fixed effects panel data regression model with spatial autocorrelation to estimate 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 at the industry level. The results suggest that interregional knowledge spillovers and their productivity effects are to a substantial degree geographically localised and this finding is consistent with the localisation hypothesis of knowledge spillovers. There is a substantial amount of heterogeneity across industries with evidence that two industries (*electronics*, and *chemical industries*) produce interregional knowledge spillovers that have positive and highly significant productivity effects. The study, moreover, confirms the importance of spatial autoregressive disturbance in the fixed effects model for measuring the TFP impact of interregional knowledge spillovers at the industry level.

Keywords. Total factor productivity, manufacturing industries, knowledge spillovers, patents, European regions, spatial econometrics

JEL Classification. C21, O33, O47, O52, R11

1 Introduction

Differences in national or regional income levels are often explained by differences in total factor productivity (TFP) (see, for example, Hall and Jones 1999; Prescott 1997). It is widely believed that technological progress plays a crucial role for productivity gains and economic growth. New growth theory, for example, emphasises that knowledge production of firms and other agents contribute to long-run economic growth because of the existence of industry-wide knowledge spillovers (see, for example, Romer 1990; Grossman and Helpman 1991). Knowledge spillovers may be defined to denote the benefits of knowledge to firms, not responsible for the original investment in the creation of this knowledge (see Fischer, Scherngell and Jansenberger 2006). Such spillovers may occur when some components of

new knowledge cannot be fully appropriated by the producer because it cannot be kept secret entirely, or because property rights do not guarantee full protection from imitation.

The last decade has seen the development of a significant body of empirical research on knowledge spillovers. Generally speaking, this research has shown that the productivity of firms or industries is related to their R&D productivity, and also to the R&D spending of other firms or other industries (see Griliches and Mairesse 1984; Mairesse and Sassenou 1991). We know, however, very little about knowledge spillovers and their productivity effects at the regional level, even though the regional dimension is particularly relevant at the European level. Fischer, Scherngell and Reismann (2007) is a notable exception that departs from previous research in two aspects: *first*, by constructing regional patent stocks to proxy industry-specific pools of interregional knowledge spillovers, and *second*, by incorporating spatial error dependence in the estimation of knowledge spillovers. The issue of spatial autocorrelation has been neglected in most studies dealing with the relationship of knowledge spillovers and productivity (see, for example, Keller 2002; Robbins 2006). Bias in this direction may lead to inefficient model coefficients as well as to biased standard errors and *t*-statistics. Based on a regional Cobb-Douglas production function Fischer, Scherngell and Reismann (2007) provide evidence that there 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 interregional knowledge spillovers. This current study is similar in spirit, but explores the relationship with industry-specific data and an explicit treatment of industry-specific knowledge stocks to provide new valuable insights.

The objective of the study is to identify knowledge spillovers that spread across regions in Europe and vary in magnitude for different industries. 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 1998-2003, and distinguish between five major industries at the two-digit level of the NACE classification system. These are *food, beverages and tobacco* (DA), *textiles and clothing* (DB, DC), *fuels and chemicals* (DF, DG, DH), *electronics* (DL), and *transport and equipment* (DM). The study implements a fixed panel data regression model with spatial error autocorrelation to estimate the effects using patent stocks as a measure of R&D output to capture the contribution of R&D (direct and spilled-over) to regional productivity at the industry level.

The remainder of the paper is organised as follows. *Section 2* outlines the framework of the study and the model to be used. *Section 3* describes the variables and the data in some detail. We use a multilateral region level relative TFP index as an approximation to the true TFP measure and patent stocks to proxy industry-specific knowledge capital stocks. *Section 4* discusses the estimation of the model and presents the estimation results, while *Section 5* concludes the paper.

2 The model

The regional Cobb-Douglas production function provides a suitable theoretical framework for our empirical analysis¹. The model used in this paper builds on an expanded version of the standard regional production function of the Cobb-Douglas type that can be written as

$$Y_{iqt} = A L_{iqt}^{\alpha_q} C_{iqt}^{\beta_q} K_{iqt}^{\gamma_{1q}} K_{iqt}^{*\gamma_{2q}} \quad (1)$$

where indices i , q and t denote the region, industry and time period, respectively. Y is some measure of output, L stands for the labour stock of the region, C for the physical capital stock, K for the region-internal stock of knowledge and K^* for the region-external stock of knowledge, i.e. for the so-called interregional knowledge spillover pool. A denotes a constant, α_q , β_q , γ_{1q} and γ_{2q} ($q = 1, \dots, Q$) are the industry-specific elasticities of output with respect to labour, physical capital, region-internal and region-external knowledge.

Dividing Equation (1) by factor share weighted physical capital and labour inputs, and assuming constant returns to scale gives the basic total factor productivity (TFP) equation in log-form that we are using in this study

$$tfp_{iqt} = \alpha + \sum_q \gamma_{1q} k_{iqt} + \sum_q \gamma_{2q} k_{iqt}^* \quad (2)$$

where $tfp_{iqt} \equiv \log TFP_{iqt}$, $\alpha \equiv \log A$, $k_{iqt} \equiv \log K_{iqt}$ and $k_{iqt}^* \equiv \log K_{iqt}^*$ for any industry $q = 1, \dots, Q$ in any region $i = 1, \dots, N$ at any point in time $t = 1, \dots, T$. The focus of interest is on

¹ See Griliches (1979) for a discussion on conceptual and empirical problems associated with the concept of knowledge capital within a Cobb-Douglas production function framework.

estimating the parameters γ_{1q} ($q = 1, \dots, Q$) and γ_{2q} ($q = 1, \dots, Q$). The γ_{1q} measure the industry-specific effects of region-internal knowledge, while the γ_{2q} capture the relative effects from region-external knowledge stocks at the industry level, i.e. the effects from industry-specific interregional knowledge spillovers.

The equation provides useful information on the long-run average relationship between knowledge and productivity in a reduced framework. It can be thought of as a industry-specific generalisation of the model given in Fischer, Scherngell and Reismann (2007) which would be a special case with $\gamma_{11} = \dots = \gamma_{1Q}$ and $\gamma_{21} = \dots = \gamma_{2Q}$.

The definition of k^* , the term capturing the impact of industry-specific interregional knowledge spillovers from any region j to region i , is given as a spatially weighted sum of the other regions' industry-specific knowledge stocks:

$$k_{iqt}^* = \sum_{j \neq i}^N k_{jqt} d_{ij}^{-\delta} \quad (3)$$

where d_{ij} denotes the geographical distance from region i to region j , measured in terms of the great circle distance [km] between the economic centres. Following the empirical literature on knowledge spillovers (see, for example, Fischer, Scherngell and Jansenberger 2006) this definition assumes that the closer regions are in geographic space, the more they can gain from each other's research effects. $\delta > 0$ is the distance decay parameter that captures the degree of localisation of interregional industry-specific knowledge spillovers. As given by Equation (3) we use a power functional form to represent the interaction process between two regions i and j .

3 The variables and the data

In this study the European coverage is achieved by using data on $i = 1, \dots, N = 203$ NUTS-2 regions of 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 (see Appendix for a detailed list of regions). The NUTS-2 level of spatial aggregation is an appropriate choice for modelling and analysis purposes and used in many other studies.

The empirical implementation of the model given by Equations (2)-(3) requires appropriate TFP and knowledge stock measures. Total factor productivity, often referred to as the residual or the index of technological progress, is defined as output per unit of labour and physical capital combined. There are several ways of measuring total factor productivity (see, for example, Nadiri 1970). TFP calculations at the industry level require real, interregionally comparable data on industry outputs, and inputs of primary factors and intermediate goods. For practical purposes, information on inputs other than physical capital and labour is not available in interregionally comparable form, so we calculate value-added TFP indices. Value-added TFP calculations are appropriate only when a well-defined, value-added function exists, which requires separability between labour, physical capital and other inputs. Consequently the TFP calculations used in this paper should be treated as approximations to the true TFP.

TFP comparisons are a classic index number problem and, thus, TFP indexes do not have a unique optimal form, but the index proposed by Caves, Christensen and Diewert (1982) is appropriate for the application in this study. This index is defined as

$$\log tfp_{igt} = (\log Y_{igt} - \overline{\log Y_{qt}}) - \sigma_{igt} (\log L_{igt} - \overline{\log L_{qt}}) - (1 - \sigma_{ikt}) (\log C_{igt} - \overline{\log C_{qt}}) \quad (4)$$

with

$$\overline{\log Y_{qt}} = \frac{1}{2} \sum_{i=1} \log Y_{igt} \quad (5)$$

$$\overline{\log L_{qt}} = \frac{1}{2} \sum_{i=1} \log L_{igt} \quad (6)$$

$$\overline{\log C_{qt}} = \frac{1}{2} \sum_{i=1} \log C_{igt} \quad (7)$$

where σ_{igt} denotes the share of labour in total production costs in region i industry q at time t . This index is equivalent to an output index where labour and physical capital inputs are held constant across regions²ⁱⁱ.

² The TFP index used is a region-relative index which implies that, for instance, a region with a calculated TFP level of 1.3 can produce 30 percent more output than the average region, with the same amount of conventional inputs (see Fischer, Scherngell and Reismann 2007). The index assumes that the regional output is characterised by constant returns to scale.

The data for calculating this industry-specific TFP index come from *Cambridge Econometrics*. Gross value added data in Euro (constant prices of 1995, deflated) are used as a measure of output Y . We adjust data on labour inputs to account for differences in average annual hours worked across countries. Neglecting differences in average annual hours worked would lead to overestimation of the productivity level in Greek and Portuguese regions, while the productivity level of Swedish and Dutch regions would be underestimated. Data on physical capital stocks is not available in the *Cambridge Econometrics* database, but gross fixed capital formation in current prices is. The perpetual inventory method has been used to generate the industry-specific fixed capital stocks applying a constant rate of ten percent depreciation and taking the mean annual growth rate which precedes the benchmark year 1998 to cover the period 1990-1998³ⁱⁱⁱ.

We use corporate patent counts^{iv4} as a proxy for the increase in (economically profitable) knowledge and derive patent stocks from European Patent Office [EPO] documents^{5v}. Our data source is the European Patent Office (EPO) database. Patents are direct outcomes of R&D processes. A patentable invention must be new, must involve an inventive step and must be capable of industrial application. We argue that an aggregation of patents is more closely related to the regional knowledge capital stock than is an aggregation of R&D expenditures or R&D capital.

Our core patent data set consists of all patents assigned to assignees located in the EU-15 countries with an application date in the years 1990-2004, totalling 655.353 patents. The patent documents provide information on the technological, geographical and temporal location (that is, their technological class, the geocoded location of the inventor(s) and the

³ The perpetual inventory method yields an estimate of the stock of fixed capital assets by estimating how many of the fixed assets installed as a result of gross fixed capital formation undertaken in previous years have survived to the current period (OECD 2001). Thus, the estimated stocks depend on the assumed depreciation rate of the annual capital flows and on the annual growth rate of gross fixed capital formations during the period previous to the observations period.

⁴ A patent is a document, issued by the Patent Office, which gives its owner an exclusive right to commercially use his/her invention for a period of up to twenty years. Patent protection means that the invention cannot be commercially made, used, distributed or sold without the patent owner's consent (WIPO 2004). Patents have been used widely in the scientific literature to capture knowledge outputs. They provide a very rich and useful source of data for the study of innovation and technological change (see, for example, Griliches 1990).

⁵ This is convenient to avoid bias due to different administrative procedures at different patent offices. Furthermore, inventors increasingly make use of the EPO as they are looking for wider geographical protection for their inventions. But nevertheless it should be noted that data on patents from the EPO cover only a subsample of patents applied for in Europe (see Fischer, Scherngell and Jansenberger 2006).

date of application). All⁶ patent applications are assigned to the region of the address of the inventor, rather than the address of the assignee, for tracing inventive activities back to the region of knowledge production. Assignment is done by using a concordance scheme between postal codes and NUTS-2 regions supplied by Eurostat. In the case of multiple inventors we follow the standard procedure of proportionate assignment^{7vi}.

To create industry-specific regional patent stocks for 1998-2003, the EPO patents were transformed by first sorting based on the year that a patent was applied for, second the region where the inventor resides, and third by industry. The latter includes matching of International Patent Classes (IPC)^{vii} with NACE industry classes. For this purpose we have used two concordance tables: MERIT's concordance table between the four-digit level of the IPC-system and the International Standard Industrial Classification (ISIC, Rev. 2) and a concordance table between ISIC (Rev. 2) and NACE provided by the United Nations (see United Nations 2007). Then for each region, the annual industry-specific patents were aggregated using the perpetual inventory method, with a constant 12 percent depreciation rate applied for each year to stock of patents created in earlier years. The assumption of a depreciation rate of 12 percent for the obsolescence of technological knowledge follows former empirical studies (see, for example, Caballero and Jaffe 1993, Robbins 2006).

4 Error specification and Model Estimation

Our data encompasses 6,090 observations (203 regions, five industries and six time periods). The estimation equations emerge by adding random errors, u_{iqt} , to Equation (2). These error terms incorporate the effects of omitted variables. Classical regression analysis assures that the omitted variables are independent of the included right-hand-side variables, and are independently, identically distributed. When using panel data, however, we can further classify the omitted variables into some groups such as region varying time- and industry-invariant, time varying region- and industry-invariant, and industry-varying region- and time invariant omitted variables.

⁶ Proportionate counting gives the interregional cooperative inventions lower weight than full counting (see Fischer, Scherngell and Jansenberger 2006).

⁷ The IPC system is an internationally developed and widely agreed non-overlapping hierarchical classification system that consists of five aggregation levels.

The estimation of Equation (2) without consideration of such effects can generate misleading results for ordinary least squares regression. In this study we restrict our attention to fixed effects estimation and assume the following two-way error components specification (see, for example, Baltagi 2001)

$$u_{iqt} = \mu_t + \nu_q + \varepsilon_{iqt} \quad (8)$$

where μ_t and ν_k are time-specific and industry-specific components, while ε_{iqt} are remainder effects. Conditional upon the specification of the variable intercept, our spatial panel data model can be estimated as fixed or a random effects model (see, for example, Elhorst 2003). A Hausman (1978) test of specification shows a test statistic of 23.31 ($p = 0.000$). The null hypothesis is rejected and we conclude that the fixed effects specification is consistent.

Under this error components specification model (2) can be written in vector form as

$$tfp = \alpha \mathbf{1}_{NQT} + \mathbf{X} \boldsymbol{\gamma} + \mathbf{Z}_\mu \boldsymbol{\mu} + \mathbf{Z}_\nu \boldsymbol{\nu} + \boldsymbol{\varepsilon} \quad (9)$$

where tfp is NQT -by-1. The observations are ordered with t being the fast running index, q the medium running index, and i the slow running index. $\mathbf{1}_{NQT}$ is a vector of ones of dimension NQT , \mathbf{X} is the NQT -by- $2Q$ matrix of explanatory variables, $\boldsymbol{\gamma}$ is $2Q$ -by-1, $\boldsymbol{\varepsilon}$ is NQT -by-1, and represents the effects of the omitted variables that are peculiar to the industry classes and time periods. We assume that ε_{iqt} can be characterised by an independently, identically distributed random variable with mean zero and constant variance σ_ε^2 . $\mathbf{Z}_\mu = \mathbf{I}_T \otimes \mathbf{1}_{NQ}$ and $\mathbf{Z}_\nu = \mathbf{I}_Q \otimes \mathbf{1}_{NT}$. \mathbf{I}_T and \mathbf{I}_Q are identity matrices of dimension T and Q , respectively. $\mathbf{1}_{NQ}$ and $\mathbf{1}_{NT}$ are vectors of ones of dimension NQ and NT , respectively, and \otimes denotes the Kronecker product.

Model (9), using the fixed effects estimator, assumes that $\boldsymbol{\mu} = (\mu_1, \dots, \mu_T)$ and $\boldsymbol{\nu} = (\nu_1, \dots, \nu_Q)$ are fixed parameters to be estimated. The fixed-effects estimator can be obtained by running the regression with time-specific and industry-specific dummy variables or by performing the within transformation and then running OLS (see Hsiao 1986). The distance decay parameter

δ which determines the extent to which region-external knowledge is effective in determining regional productivity, is identified from variation of the productivity effects of knowledge capital in other regions conditional on bilateral distance (see Equation (3)). δ is optimised with respect to the log-likelihood function using Brent's direct search procedures (see Press et al. 1992).

Table 1 Estimates of the total factor productivity model with time-specific and industry-specific fixed effects

	Fixed effects estimates	Fixed effects estimates with spatial error autocorrelation
Parameter estimates (<i>p</i>-values in brackets)		
<i>Constant</i> [α]	-0.105 (0.000)**	-0.165 (0.000)**
<i>Internal knowledge capital stocks</i>		
Food and beverages [γ_{11}]	0.057 (0.000)**	0.027 (0.007)*
Textiles and clothing [γ_{12}]	0.009 (0.468)	-0.006 (0.630)
Fuels and chemicals [γ_{13}]	0.039 (0.171)	0.024 (0.008)*
Electronics [γ_{14}]	0.280 (0.000)**	0.241 (0.000)**
Transport and equipment [γ_{15}]	-0.102 (0.132)	-0.100 (0.098)
<i>Interregional knowledge spillovers</i>		
Food and beverages [γ_{21}]	0.071 (0.665)	0.075 (0.284)
Textiles and clothing [γ_{22}]	-0.262 (0.254)	-0.271 (0.303)
Fuels and chemicals [γ_{23}]	0.380 (0.000)**	0.297 (0.000)**
Electronics [γ_{24}]	0.951 (0.000)**	0.925 (0.000)**
Transport and equipment [γ_{25}]	-0.884 (0.000)**	-0.899 (0.113)
<i>Distance decay parameter</i> [δ]	1.095	0.647
<i>The spatial autoregressive parameter</i> [λ]	—	0.303 (0.000)**
Likelihood ratio test statistic	—	-292.512 (0.000)**
Log Likelihood	-5,331.383	-5,162.119
Adjusted R²	0.203	0.264
Sigma Square	0.337	0.311

Notes: The dependent variable is the multilateral industry-specific TFP index, as defined in the text. γ_{1q} ($q = 1, \dots, 5$) measures the effect of industry-specific region-internal stocks of knowledge, while γ_{2q} determines the strength of industry-specific interregional knowledge spillover effects on productivity. δ – implicit in the construction of out-of-region-external industry-specific stocks of knowledge capital – defines the distance effects and is optimised with respect to the log-likelihood function using direct search procedures. ** denotes significance at the 0.001 significance level, and * significance at the 0.05 significance level.

The resulting estimates are reported as fixed effects estimates in Table 1. γ_1 measures the (elasticity) effect of the region-internal knowledge stocks on productivity, while γ_2 captures

the relative elasticity from out-of-region stocks of knowledge. A positive and significant γ_{2Q} ($q = 1, \dots, Q$) is interpreted as evidence of cross-region knowledge spillovers from industry q . For two industries ($q = 3, 4$) – *fuels and chemicals*, and *electronics* – there are significant and positive parameter estimates. For these industries, this suggests the presence of interregional knowledge spillovers and that these spillovers contribute to regional TFP. A one percent increase in the spatially weighted out-of-region patent stocks in *electronics*, for example, leads to a 0.951 percent increase in relative TFP which supports the hypothesis that *electronics* provide important enabling technologies for the arising knowledge based economy. This is preliminary evidence that holding the level of knowledge activities constant within a region, the increase in knowledge stock in nearby regions has a positive effect on industry-level productivity. The distance decay or localisation parameter δ is estimated to be equal to 1.095, indicating that interregional knowledge spillovers from *electronics*, and *fuels and chemicals* are to a substantial degree geographically localised, i.e. they increase with geographic proximity.

But the fixed effects estimates ignore spatial autocorrelation due to neighboring regions. The second column in Table 1 gives the fixed effects estimates with spatial error autocorrelation using maximum likelihood estimation. We assume the error term ε in Equation (9) to follow a standard first-order spatial autoregressive process with a scalar spatial autoregressive coefficient $|\lambda| < 1$ and a conventional binary spatial weights matrix^{8viii} (see Anselin 1988). These ML estimates were obtained by using the *errorsarlm* procedure of Bivand's *spdep package*^{9ix} in combination with Brent's direct search procedure (see Press et al. 1992). For technical details of the estimation approach see Fischer, Scherngell and Reismann (2007).

The MLE estimates accounting for spatial autocorrelation do not differ much from the fixed-effects estimates ignoring spatial autocorrelation. The γ_{23} and γ_{24} estimates provide evidence for the presence of interregional knowledge spillovers for the industries *electronics*, and *fuels and chemicals*. The λ estimate is equal to 0.303, with a standard error of 0.029. A likelihood ratio test of $\lambda = 0$ yields a χ_1^2 test statistic of 292.512. This is statistically significant and confirms the importance of a spatial disturbance term in the fixed-effects model for

⁸ In this study, the spatial weights matrix is constructed so that a region sharing a common border takes the value of one and zero otherwise.

⁹ Source package: *spdep* 0.3-17 retrieved from <http://cran.r-project.org/src/contrib/Descriptions/spdep.html>.

measuring the total factor productivity effects of interregional knowledge spillovers. The distance decay parameter δ is estimated to be 0.647. When spatial autocorrelation is not taken account the degree of geographical localisation of knowledge spillovers is overestimated. Incorporation of spatial error dependence decreases the estimated distance decay parameter by about 41 percent.

5 Summary and Discussion

The objective of this paper was to estimate TFP effects of interregional knowledge spillovers in manufacturing industries across European regions. We used patent stocks constructed from EPO patent applications as a proxy for a region's industry-specific knowledge capital stock and the TFP index suggested by Caves, Christensen and Diewert (1982) to measure productivity effects of industry-specific interregional knowledge spillovers in a spatial panel data model framework with fixed effects.

The analysis has produced a number of interesting results. *First*, geographic distance appears to have a strongly limiting effect on knowledge spillovers among regions. This suggests that interregional knowledge spillovers and their productivity effects are to a substantial degree geographically localised and this finding is consistent with the localisation hypothesis of knowledge spillovers. *Second*, the study provides evidence that a region's total factor productivity depends not only on its own knowledge capital but also on interregional knowledge spillovers. *Third*, there is a substantial amount of heterogeneity across industries. There is evidence that two industries (*electronics*, and *chemical industries*) produce cross-region knowledge spillovers that have positive and highly significant productivity effects. The coefficients on spatially weighted, out-of-region stocks of knowledge from *foods and beverages*, *textiles and clothing*, and *transport and equipment* are not significant. *Finally*, the analysis confirms the importance of spatial autoregressive disturbance in the fixed effects model for measuring the TFP impact of interregional knowledge spillovers at the industry level.

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Appendix

The sample of regions 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. Liège; 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; Andalucía; 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