Economic Systems xxx (2015) xxx–xxx

Contents lists available at ScienceDirect

Economic Systems

journal homepage: www.elsevier.com/locate/ecosys

The impact of knowledge spillovers on total factor productivity revisited: New evidence from selected European capital regions

Paula Puškárová[a,*], Philipp Piribauer[b,*]

[a] University of Economics in Bratislava, Institute for Economics and Management, Dolnozemska cesta 1/b, 852 35 Bratislava, Slovakia
[b] Vienna University of Economics and Business, Institute for Economic Geography and Geoinformatics, Welthandelsplatz 1, A-1020 Vienna, Austria

ARTICLE INFO

Article history:
Received 14 November 2014
Received in revised form 8 September 2015
Accepted 25 September 2015

JEL classification:
O330
O470
R120

Keywords:
Knowledge capital
Knowledge spillovers
Knowledge production function
Total factor productivity
NUTS-2
Spatial panel

ABSTRACT

This paper aims at identifying the contribution of knowledge capital to total factor productivity differences among European sub-national regions within a spatial econometric regression framework. Special emphasis is laid on the estimation of interregional spillovers between the Western and Eastern European regions, focusing on the triangle of capital regions Vienna-Budapest-Bratislava. By accounting for human capital stocks, the results suggest lower spillover effects emanating from patent activities. Moreover, Vienna appears to be the largest contributor to productivity increases in Bratislava. Budapest's productivity seems to be sensitive to the knowledge and human capital endowments of the EU, but less so to those of Vienna.

1. Introduction

The recent empirical literature on economic growth has shown that differences in economic income, both at national and sub-national levels, are mainly due to disparities in total factor productivity (TFP) (Klenow and Rodriguez-Clare, 1997; Easterly and Levine, 2001; Jerzmanowski, 2007). Economic theory highlights that the technological process plays an important role in productivity gains and economic growth (Prescott, 1997; Hall and Jones, 1999). The work by Griliches (1979), for example, augments the production model with the stock of knowledge. Moreover, growth theory emphasizes that the knowledge production of firms contributes to long-run growth, especially because of knowledge spillovers. Fischer et al. (2009) define knowledge spillovers as the benefits of knowledge to firms, industries or regions not responsible for the original investment in the creation of this knowledge. Knowledge spillovers therefore represent external flows of knowledge.

Fischer et al., 2006 distinguish two types of knowledge spillovers: First, pecuniary externalities, which denote spillovers embodied in traded capital or intermediate goods and services, and second, non-pecuniary externalities, which denote

* Corresponding authors.
E-mail addresses: paula.puskarova@euba.sk (P. Puškárová), philipp.piribauer@wu.ac.at (P. Piribauer).

http://dx.doi.org/10.1016/j.ecosys.2015.09.006
0939-3625/

spillovers of the disembodied kind. The paper follows the spirit of Fischer et al. (2006) and Fischer et al. (2009), among others, and considers spillovers of the disembodied kind.

In addition to considering the stock of knowledge as a factor explaining differences in regional total factor productivity, this paper extends the knowledge capital model with human capital (see Mankiw et al., 1992). This seems to be particularly important since human capital not only measures the potential of performing knowledge-intensive economic activities, but may also condition a regions' absorptive capacity. A second motivation for including human capital is a more practical one. Many theoretical as well as empirical studies on regional economic growth have demonstrated the central role of human capital in explaining growth differences (LeSage and Fischer, 2008; Fischer, 2011; Cuaresma and Feldkircher, 2013; Cuaresma et al., 2014). Since several proxies of knowledge and human capital stocks are likely to be highly correlated, failing to account for human capital in an empirical knowledge capital model might lead to severe omitted variable bias.

The key issue is to distinguish between knowledge and human capital. The Cobb-Douglas production function considers both factors of growth in a straightforward manner (for example, Ishise and Sawada, 2009). However, knowledge production functions (Jones, 1995) see human capital as the decisive input factor, whereas knowledge is the output. On the other hand, the concept of human capital can be traced to the earnings-schooling function. A long line of studies in the Mincer tradition demonstrated that investments into schooling pay off. Education has thus emerged as the first proxy for human capital. However, the true impact of education on productivity, while controlling for knowledge capital, is still being debated. Schultz' (1960) estimates suggested that about one fifth of TFP growth can be attributed to changes in human capital. The robustness of these results was checked by Jorgenson and Griliches (1967) using education attainment. Even though later studies proved this estimate to attenuate over the years, there is a general consensus that human capital is to a large extent linked to the education process and factors into many knowledge producing and absorbing activities. However, it is still rather challenging to properly discern between both types of capital because a part of knowledge never takes some disembodied measurable form such as a patent. Some knowledge, such as a productivity-enhancing organizational structure, may be reflected only as the know-how of a company, possibly appearing in the records as expenses for the training of employees with respect to the new organizational structure. In line with this concern, the estimated impacts of human capital might capture some part of the knowledge capital impacts.

This paper attempts to quantify the contribution of both knowledge and human capital to differences in total factor productivity among European regions within a regression framework in general, and the impacts of their spatial spillovers to other regions in particular. Since classical linear regression frameworks treat the observations/regions as being independent of each other, these approaches appear to be inappropriate for capturing spatial spillovers. This paper therefore uses spatial econometric estimation approaches (see LeSage and Pace, 2009) to account for spatial spillovers for both human and knowledge capital.

Moreover, the paper focuses particularly on exploring spillovers among Western and Eastern European regions. For this purpose, in an empirical illustration we investigate human and knowledge spillover effects in the triangle of the capital regions Bratislava, Vienna and Budapest, since they represent both the Western and Eastern parts of the European Union. Due to their spatial proximity, the triangle of these three capital city regions appears to be particularly interesting for studying spatial spillover effects.

The remainder of the paper is organized as follows: in the next section, we introduce the theoretical model and its empirical specification. Next, we explain the sources and construction of the data. In the fourth section, we present the estimation results. Subsequently, we show the strength of spillover effects amongst the selected capital regions. Our concluding remarks are summarized in Section 6.

2. Model

In order to address our research question, we need to build a rather general model that will allow us to estimate spillover effects between each pair of regions. Let K_{it} and H_{it} denote the knowledge and human capital stocks at time $t = 1, \ldots, T$ and region $i = 1, \ldots, N$. We follow Jones (1995) and assume that knowledge production ΔK_{it} is a function of human capital H_{it} with some R&D productivity δ_{it}, and the region-specific knowledge capital stock in the previous period:

$$\Delta K_{it} = \delta_{it} K_{it}^{\gamma} H_{it}^{\beta} \exp(\omega_{it}) \tag{1}$$

$\exp(w_{it})$ is an error term. β and γ are elasticities associated with the human and knowledge capital stock, respectively.

Building on an expanded version of the standard Cobb-Douglas regional production function, the model can be written as:

$$Y_{it} = \delta_{it} K_{it}^{\gamma} H_{it}^{\beta} L_{it}^{a} C_{it}^{1-a} \exp(\varepsilon_{it}), \tag{2}$$

where Y_{it}, L_{it} and C_{it} denote regional output, labor stock, and physical capital stock, respectively. The error term e_{it} reflects all random factors of output and productivity and is assumed to be identically and independently distributed with mean zero and variance σ^2. α, $1-\alpha$, $\gamma\beta$ are the output elasticities of labor, physical capital, knowledge and human capital, respectively.

Following endogenous growth models (Ertur and Koch, 2007), the knowledge capital stock K_{it}^{γ} is assumed to consist of intra-regional knowledge $K_{it}^{\gamma_1}$ as well as region-external knowledge $K_{jt}^{\gamma_2}$ for $j \neq i$. Similarly, the human capital stock H_{it}^{β} is also given by the own regional stock $H_{it}^{\beta_1}$ and the region-external human capital $H_{jt}^{\beta_2}$. By calculating TFP in the usual way as $F_{it} = \frac{Y_{it}}{(L_{it}^{\alpha} C_{it}^{1-\alpha})}$, we arrive at the following expression:

$$F_{it} = \delta_{it} K_{it}^{\gamma_1} H_{it}^{\beta_1} \sum_{j \neq i}^{N} K_{jt}^{\gamma_2} \sum_{j \neq i}^{N} H_{jt}^{\beta_2} \exp(\varepsilon_{it}) \tag{3}$$

Recently, spatial econometric models have gained popularity in the empirical regional science literature. Using such models, spillovers between regions can be explicitly taken into account. The recent literature on spatial autoregressive models has moreover shown that neglecting to account for spatial dependence among regions might result in severe omitted variable bias (see LeSage and Pace, 2009). In accordance with the spatial point of view, the spillovers from a region *i* to a region *j* are subject to a concept of closeness (neighborhood). The neighborhood of regions *i* and *j* is captured in an *N* times *N* non-negative spatial weight matrix *W*. Specifically, $W_{ij} > 0$, if regions *i* and *j* are assumed to be neighbors. Moreover, $W_{ii} = 0$, since no region is assumed to be a neighbor to itself. In this context, we denote regional-external knowledge $K_{jt}^{\gamma_2}$ and human$H_{it}^{\beta_2}$capital stocks as follows:

$$K_{it}^{\gamma_2} = \left[\sum_{j \neq i}^{N} W_{ij} K_{jt} \right]^{\gamma_2} \tag{4}$$

$$H_{it}^{\beta_2} = \sum_{j \neq i}^{N} W_{ij} H_{jt}]^{\beta_2} \tag{5}$$

As already mentioned, both knowledge and human capital refer to broadly defined concepts, and in the empirical literature they are usually only represented by weak proxies. Quality of education, skills acquired outside formal education, and non-patentable knowledge are just a few examples of factors that are hard to capture. Following Ertur and Koch (2007), these omitted variables are presumably also spatially correlated and thus have to be captured using a spatial lag specification either in the error term (Spatial Durbin Error Model (SDEM) specification) or in the dependent variable (Spatial Durbin Model (SDM) specification). We assume that all the omitted variables are endogenous to knowledge capital, as they are to TFP, so that the SDM specification appears to be more appropriate (see LeSage and Pace, 2009). Therefore, we introduce the spatial autocorrelation term in TFP–$\sum_{j \neq i}^{N} W_{ij} F_{jt}$with the scalar spatial autoregressive parameter *r*.

Apart from the process of knowledge generation, we have to consider the presence of certain temporal factors. We are interested in estimating effects throughout the first decade of the 2000s. However, the integration of post-Communist economies into the European Union in 2004 and 2007 and the global financial crisis might introduce some bias into our estimates (Elhorst, 2012). In order to account for potential structural changes, we decided to include time-period fixed effects in our empirical version of the model as well.

After taking logs, we can rewrite the model from Eq. (3) as follows:

$$\ln F_{it} = \rho \left[\sum_{j \neq i}^{N} W_{ij} \ln F_{jt} \right] + \beta_1 \ln H_{it} + \gamma_1 \ln K_{it} + \beta_2 \left[\sum_{j \neq i}^{N} W_{ij} \ln H_{jt} \right] + \gamma_2 \left[\sum_{j \neq i}^{N} W_{ij} \ln K_{jt} \right] + \xi_{it} \iota + \varepsilon_{it} \tag{6}$$

where spatial time-period fixed effects x_{it} account for impacts of various temporal disturbances. With Eq. (6), our model takes the form of a spatial Durbin panel model, which is characterized by a spatial lag both in the dependent variable and in the explanatory variables. We expect that all estimated slope coefficients turn out to be positive, so that both knowledge and human capital that are available locally and in the neighborhood contribute positively to the total factor productivity levels across the EU regions.

3. Data

One challenge for this study is to construct the TFP data in a robust manner. As Katayama et al. (2009) show, manipulation with the primary (entry) variables introduces large variation in the calculated TFP. Conventionally, the TFP values are derived from $\ln F_{it} = \ln Y_{it} - s_{it} \ln L_{it} - (1 - s_{it}) \ln C_{it}$. In a line of studies, Y_{it} is represented simply by gross domestic product (GDP), L_{it} stands for the number of people employed and C_{it} for investments. However, those studies lead to conflicting and ambiguous results. We follow an approach proposed by Fischer et al. (2009), who attempt to correct the robustness of the TFP calculus in several aspects. First, they suggest to employ gross value added (GVA) instead of GDP. One argument here is that GDP encompasses all kinds of production effects, while the GVA concept is more knowledge-centered, which is similar to the TFP concept. Second, the labor input share s_{it} can be better calculated from the labor costs than from its revenues, particularly in the case of imperfect factor shares. Third, the C_{it} should be seen as a stock rather than a mere flow, since the positive benefits from investments do not usually occur within a period (in our case, within a year). The stock of investments can then be derived from gross investments I_{it} using the perpetual inventory method given by $C_{it+1} = C_{it}(1-r) + I_{it+1}$. The depreciation rate of the stock of investments r is assumed not to change significantly over the years.

All the TFP-entry variables were taken from the Cambridge Econometrics Database. The GVA in the database is in constant Euro prices of 2000 and deflated, investments are in current prices in Euro, its depreciation rate is presumably $r = 0.12$ (Fischer et al., 2009), and labor costs are wage remunerations in Euro in current prices. The labor share is then given by the share of wage remunerations in total wage remunerations plus investments. In order to partial out the effects of working time differences across the EU regions, we adjusted the wage remunerations by hours worked.

Following this approach, we have constructed a vector of log-transformed TFP values, where 168 NUTS-2 regions have higher and 83 have lower TFP levels than the average EU NUTS-2 region. The top five regions with the highest TFP levels are in Luxembourg (1.7518), Stockholm (1.6955), Inner London (1.6942), Groningen (1.6267) and Brussels (1.5991). Among the five regions with the lowest TFP levels are regions in Romania and Bulgaria. This paper is concerned about the knowledge spillovers fostering West-East EU convergence. For that purpose, we selected the regions of Bratislava (Slovakia), Budapest (Hungary), Brno (Czech Republic) and Györ (Hungary), which are all capital or large city regions located uniquely close to one capital from the Western EU: Vienna (Austria). Fig. 1 depicts the TFP levels for the selected regions compared to the average regional TFP levels across the EU.

In terms of TFP, Fig. 1 shows that Bratislava and Budapest did catch up with the Vienna region, especially after the EU accession of Slovakia and Hungary in 2004. The figure supports our hypothesis that the selected area has been experiencing fast-growing knowledge spillovers, even though these are less tractable for the non-capital regions of Brno and Györ. The significance of knowledge and human capital spillovers for the TFP catch-up process will be scrutinized in Section 5.

Equally important for the robustness of our results is the selection of the knowledge and human capital variables. In the literature, we merely encounter weak proxies. Knowledge capital is often represented by stocks of patent applications and human capital by population with tertiary education. However, there is objectively a large pool of tacit knowledge which is not captured by patent stocks. As Griliches (1990) posits, this knowledge remains unpatented as costs are too high, knowledge is strongly context-related, the inventor gets discouraged by the administration burden associated with patent registration, or the conditions for a patent application are simply not met. Examples of non-patentable innovations could be an own organizational setting or a successful motivational technique. Even though they increase labor productivity, they are often context-related and the innovator feels less driven to protect them. Moreover, many patents are just upgrades of already existing patents and as such they may increase productivity less than a single patent of a revolutionary nature. In other words, the productivity accrual for different patent applications varies considerably. However, no better proxy for knowledge capital has been deployed so far, and therefore we decided to limit knowledge capital purely to patentable knowledge.

As a proxy of knowledge capital, we use patent stocks calculated from patent applications to the European Patent Office (EPO), again using the perpetual inventory method. Therefore, the patent stock of region i at the end of period $(t+1)$ is given by $K_{it+1} = K_{it}(1-r) + P_{it+1}$, where K_{it} is the stock of knowledge embodied in EPO patent applications at the end of period t and r is the depreciation rate of that knowledge stock. The number of EPO patent applications was taken from the Eurostat Regional Databases. The Greek regions were excluded because of data scarcity. The depreciation rate r=0.12 was used, following the study of Caballero and Jaffe (1993). When searching for a human capital proxy, we faced the challenge of capturing all sorts of skills, such as the abilities to socialize or create networks of knowledge transmissions, or personal discipline at work. In general, the proxy for human capital should reflect the ability to contain marketable knowledge and move it around. Conventionally, there are three milestones throughout the education life. The first is when a person completes elementary education, the second when a person completes full secondary education (finishing with some sort of state examination), and the third relates to the graduation from college or university. An important part of education is life-long training, which, however, only further upgrades the skills received at the highest completed stage of education and as such may not factor into our estimates significantly. In terms of tertiary education facilities, the quality of education differs considerably across the EU (following the results of the Shanghai University Ranking or the Financial Times Ranking). However, at the secondary

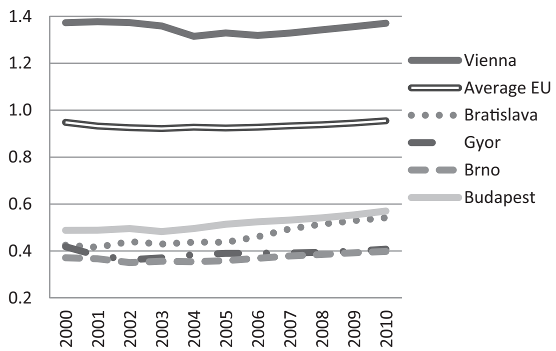

Fig. 1. Trajectory of TFP in the selected regions.

stage of education, PISA surveys demonstrate that European human capital is comparable in terms of maths and reading as well as research literacy. PISA surveys are performed on a sample of 15-year-olds. In light of this, we decided to take the working age population and filter the low educated share out. Thus, human capital *H* shall be represented by the share of the population aged 25–64 with at least full secondary education attainment (completed ISCED 3–6 level) in this paper. The empirical literature agrees with this approach. Other human capital proxies (such as the share of tertiary educated population or the number of schooling years) perform confusingly in growth regressions. Again, the data was taken from the Eurostat Regional Databases. A detailed summary of the data is provided in Table 1.

We chose to run the estimations at the level of NUTS-2 regions covering the 26 EU countries. Data availability limited us to perform the estimations on a smaller spatial scale. The NUTS (Nomenclature of territorial units for statistics) classification is a hierarchical system for dividing up the economic territory of the EU for the purposes of statistical collection of data and framing the cohesion policy of the EU. There are three levels, NUTS-1 to NUTS-3, where the regions are separated according to the regional administrative division of a country. In our sample, most NUTS-2 regions are located in Germany (39), United Kingdom (37), France (22), Italy (21) and Spain (17). The countries of Estonia, Latvia, Lithuania, Luxembourg, Malta and Cyprus are represented by a single NUTS-2 region. Though varying in size, they are generally considered to be appropriate spatial units for modeling purposes. In most cases, they are moreover sufficiently small to capture sub-national variations. But we are aware that NUTS-2 regions are formal rather than functional regions, and their delineation does not represent the boundaries of regional growth processes very well.

The spatial weight matrix may be based on two neighborhood concepts: a common border or distance. In case of a common border, each element of the spatial weight matrix is set to unity if the two regions share a common border and zero otherwise. Although this determination is rather straightforward, it neglects spillovers from regions delineated as islands. An alternative approach is to take distances between regions and assume distance decay of spillover effects. In our case, we employ this approach and denote each element of the spatial weight matrix as $W_{\text{ij}} = d_{ij}{}^{-2}$ with no distance bound. As a spatial weight matrix is built to capture the extra-regional impacts of explanatory variables, its main diagonal elements (neighborhood of the same region) are set equal to zero: $W_{ii} = 0$. In order to build up the distance decay spatial weight matrix, we take distance d_{ij} as the distance between the *i*'s centroid and the *j*'s centroid. The longitude and latitude of each region was taken from the GISCO Eurostat database. The spatial weight matrix was row-standardized to avoid overestimation problems (Elhorst, 2012).

4. Spatial panel estimation

We organized our data into a spatial Durbin panel model. Spatial panel models contain time series observations for a number of geographical units in order to assess impact estimates across both space and time. In our case, we consider $N = 251$ European NUTS-2 regions and $T = 11$ years. We estimate an SDM model with time-period fixed effects as demonstrated in Eq. (6), using the MATLAB package developed by Paul Elhorst, which is available under http://www.

Table 1
Descriptive and summary statistics, averages over 2000–2010 and all regions.

Variable	Proxy	Source	Mean	Standard deviation
H	Share of population aged 25–64 with at least secondary education attainment (ISCED 3–6)	Eurostat online databases	70.4	15.2
K	Knowledge Capital (ln)	Own calculation[b]	5.7	2.0
P	EPO patent applications p.c.	Eurostat online databases	202.9	379.9
F	Total Factor Productivity (ln)	own calculation[a]	−0.2	0.5
Y	Gross Value Added (mil EUR, constant 2000 prices, deflated)	Cambridge Econometrics	49,328.0	63,479.0
L	Labor	Own calculation[d]	44,148.0	45,086.0
E	Employment (number of employees)	Cambridge Econometrics	1,162.0	1,193.0
W	Hours Worked	Cambridge Econometrics	38.0	3.0
C	Investments Stock (mil EUR, constant 2000 prices, deflated)	Own calculation[c]	61,772.0	78,577.0
I	Investments (mil EUR, constant 2000 prices, deflated)	Cambridge Econometrics	10,675.0	13,461.0
s	Labor Input Share (%)	Own calculation[e]	71.5	5.6
R	Remuneration (mil EUR)	Cambridge Econometrics	28,889.0	37,367.0

[a] Calculated as $\ln F_{it} = \ln Yit - s_{it} \ln L_{it} - (1 - s_{it}) \ln C_{it}$.
[b] Calculated from yearly P using perpetual inventory method denoted as $K_{it+1} = K_{it}\,(1\text{-}r) + P_{it+1}, r{=}0.12$.
[c] Calculated from yearly I using perpetual inventory method denoted as $C_{it+1} = C_{it}\,(1\text{-}r) + I_{it+1}$, $r{=}0.12$.
[d] Calculated as E*W.
[e] Calculated as R/(R + I).

Table 2
Estimation results: Spatial Durbin model specification.

Determinants	SDM time-period fixed effects, distance decay W	
ρ (spatial lag in TFP)	0.835848	(0.000000)
γ_1 (patent stocks – K)	0.088384	(0.000000)
β_1 (secondary educated – H)	0.080801	(0.008805)
γ_2 (spatial lag in K)	0.025600	(0.000000)
b_2 (spatial lag in H)	−0.216494	(0.000000)
σ^2	0.0334	
pseudo R^2	0.8820	
adjusted R^2	0.7639	
logL	658.9787	
Wald test spatial lag	317.9059	(0.0000)
LR test spatial lag	197.3773	(0.0000)
Wald test spatial error	451.0423	(0.0000)
LR test spatial error	188.0979	(0.0000)
Hausman t-statistics	1044.7930	(0.0000)

Notes: p-value in parentheses; pseudo R^2 represents a measure of the goodness of fit; adjusted R^2 includes punishment on the dimension of the model.

regroningen.nl/elhorst/software.shtml. Based on work by Yu and Lee (2010), the estimation procedure involves a maximum likelihood estimation (MLE) approach in order to obtain estimates for the unobservable model parameters of interest.

Table 2 shows the results of the spatial panel model estimation for the parameters ρ, β_1, γ_1, β_2, γ_2 related to the spatial lag in TFP, human and knowledge capital and their spatial lags, respectively. The results demonstrate strong autocorrelation in the dependent variable. Both the Likelihood Ratio (LR) and Wald tests point out that the spatial lags in the exogenous variables should not be omitted in favor of a spatial lag model. Lower values of the Wald and LR tests in the SDM setting as compared to the SDEM specification indicate that the SDM model specification appears to be more appropriate for our dataset.

It is worth noting that in conventional (non-spatial) linear models, parameter estimates have a straightforward interpretation. LeSage and Pace (2009), however, show that the interpretation of the parameter estimates in spatial autoregressive models might lead to erroneous conclusions. This is due to the non-linear nature of models involving a spatial lag in the dependent variable. Moreover, spatial autoregressive models typically exhibit non-zero cross-partial derivatives. The non-linear nature of spatial autoregressive model specifications implies that changes in a region's patent stock affect not only the TFP in the same region (direct effects), but also the TFP in other regions (indirect or spillover effect). Due to non-negative spillover effects, spatial autoregressive models involve dealing with N^2 partial derivatives for a particular explanatory variable. The $N \times N$ matrix of partial derivatives of the expected elasticity of TFP with respect to patent stocks K in a region $i = 1, \ldots, N$ is given by:

$$\left[\frac{\partial EF)}{\partial K_1} \quad \cdots \quad \frac{\partial EF)}{\partial K_N}\right] = I - \rho W)^{-1} \begin{bmatrix} \gamma_1 & W_{12}\gamma_2 & \cdots & W_{1N}\gamma_2 \\ W_{21}\gamma_2 & \gamma_1 & \cdots & W_{2N}\gamma_2 \\ \cdots & \cdots & \cdots & \cdots \\ W_{N1}\gamma_2 & W_{N2}\gamma_2 & \cdots & \gamma_1 \end{bmatrix} \tag{7}$$

(see LeSage and Pace, 2009), where W_{ij} is the (i,j) th element of the spatial weight matrix W. In order to deal with this overwhelming amount of information, LeSage and Pace (2009) suggest reporting a summary metric for the indirect (spillover) effects, measured by the average of either the row or the column sums of the off-diagonal elements of the matrix. A summary metric for direct impacts is represented by the average of the diagonal elements of the matrix. In compliance with this approach, Table 3 reports the average direct and indirect (spillover) impact estimates.

The table highlights the differences in TFP elasticities on our proxies of knowledge and human capital. The elasticity of TFP on domestic patent stocks appears to be positive and significant. The estimated indirect (spillover) effects from patent stocks are also positive and significant. The population share with at least full secondary attainment is both significant and positive for domestic and foreign TFP levels, but the spillover effects appear to be considerably larger in magnitude as compared to the direct and indirect impacts from patent stocks. The estimated average indirect impacts suggest that a one percent increase in a regions' human capital stock implies an increase in the TFP of all other regions by 0.46 percent. The spillover effects of EPO patent application stocks amount to 0.19 percent. It is worth noting that this result appears to be higher in magnitude than the estimate of knowledge spillover impacts in Fischer et al. (2009), which amounts to 0.1. However, Fischer et al. (2009) considered only the Western European regions spanning the period until the EU enlargement in 2004. Due to the technology gap between Eastern and Western Europe, our results indicate that the EU enlargement was indeed accompanied by intensifying knowledge transfers.

Table 3
Direct and indirect effects estimates based on the coefficient estimates of the spatial Durbin model as reported in Table 2.

	Patent stocks (K)		Secondary educated workforce (H)	
Direct Effects	0.100604	(0.000000)	0.062030	(0.049789)
Indirect Effects	0.595103	(0.000000)	0.831321	(0.000000)
Total Effects	0.695707	(0.000000)	0.895531	(0.000000)

Note: *p*-value in parentheses.

Even though our results struggle to answer the question whether productivity gains are attributable to the cross-border transmission of non-patentable knowledge, the empirical analysis detects a strong responsiveness of TFP levels to human capital endowments across European regions. The effects from conventional knowledge capital stocks are smaller, which may be attributable to diminishing returns to scale in the R&D sector (Jones, 1995). A higher amount of knowledge capital, however, also induces fishing-out effects, thus leading to decreasing gains in productivity.

Our results were exposed to several robustness checks. First, following Katayama et al. (2009), we redid the TFP calculations for different depreciation rates of physical capital. We re-estimated the model for the 5.5% rate as proposed by Görzig (2007) and Hernández and Mauleón (2005) and for the 8% rate, following the results in Oulton and Srinivasan (2003). Second, we reproduced the estimations for various specifications of the spatial weight matrix, namely for four and eight nearest neighbors, and a spatial weight matrix of five nearest neighbors constructed by means of travel time distances. Moreover, we tested alternative specifications of the model, namely an SDM model with two-way fixed effects and SDEM specifications with either spatial, time-period or two-way fixed effects. The results are summarized in Tables 4–6 . Our estimates, however, appear to be quite robust.

5. Interregional spillovers in the capital regions of Bratislava-Vienna-Budapest

As already noted in the previous section, conditional on an explanatory variable, the indirect (spillover) effects between two different regions correspond to a particular off-diagonal element of the impact matrix. Each diagonal element of the impact matrix denotes a region's direct effect.

Based on the fact that we used the maximum likelihood approach to produce parameter estimates, the estimated parameters correspond to the mean values of a normal distribution. However, since the impact estimates of interest are non-linear functions of parameter estimates, the inference on direct and indirect impact estimates is more complicated.

We thus follow a simulation approach proposed by LeSage and Pace (2009). If we draw D parameters from a normal distribution with its moments given by the maximum likelihood estimation output, D average (direct or indirect) effects can be calculated. If φ_{kd} denotes the effect of the k-th explanatory variable of draw $d = 1, \ldots, D$, the mean φ_k, variance v_k and the corresponding t-value τ of the D draws are given by:

$$\overline{\varphi}_k = \frac{1}{D}\sum_{d=1}^{D} \varphi_{kd} \tag{8a}$$

Table 4
Robustness checks: Alternative specification of spatial weight matrix, TFP construction.

	Depreciation rate of K = 5.5%	W–4 nearest neighbors	W–8 nearest neighbors	W–nearest 5 at travel distance
ρ (spatial lag in TFP)	0.123453	0.574851	0.617362	0.725634
	(0.000000)	(0.000000)	(0.000000)	(0.000000)
γ_1 (patent stocks – K)	0.088844	0.081224	0.084413	0.094822
	(0.000000)	(0.000000)	(0.000000)	(0.000000)
β_1 (sec. educated – H)	0.042655	0.093454	0.080740	0.116828
	(0.251085)	(0.002634)	(0.011400)	(0.000051)
γ_2 (spatial lag in K)	0.099149	0.048466	0.036822	−0.009133
	(0.000000)	(0.000000)	(0.000000)	(0.048051)
β_2 (spatial lag in H)	0.219570	0.277026	0.223254	0.268718
	(0.000000)	(0.000000)	(0.000000)	(0.000000)
σ^2	0.0489	0.0342	0.0361	0.0294
pseudo R^2	0.8330	0.8787	0.8719	0.8958
adjusted R^2	0.7439	0.7927	0.7960	0.7954
logL	217.45145	605.31168	585.19833	735.84507

Notes: *p*-value in parentheses, H stands for the share of working age population with completed full secondary (ISCED 3–6) education; pseudo R^2 represents a measure of the goodness of fit; adjusted R^2 includes punishment on the dimension of the model.

Table 5
Direct and indirect effects estimates based on the coefficient estimates reported in Table 4.

	depreciation rate of K = 5.5%	W–4 nearest neighbors	W–8 nearest neighbors	W–5 nearest at travel distance
Direct effects – *K*	0.104626	0.095369	0.093282	0.107947
	(0.000000)	(0.000000)	(0.000000)	(0.000000)
Indirect effects – *K*	0.185906	0.209778	0.223558	0.204260
	(0.000000)	(0.000000)	(0.000000)	(0.000000)
Total effects – *K*	0.290532	0.305147	0.316840	0.312207
	(0.000000)	(0.000000)	(0.000000)	(0.000000)
Direct effects – *H*	0.090988	0.060664	0.063525	0.076230
	(0.003094)	(0.037865)	(0.038760)	(0.005168)
Indirect effects – *H*	0.435819	0.492490	0.437199	0.478242
	(0.000000)	(0.000000)	(0.000000)	(0.000000)
Total effects – *H*	0.526807	0.553154	0.500726	0.554472
	(0.000000)	(0.000000)	(0.000000)	(0.000000)

Note: *p*-value in parentheses.

Table 6
Robustness checks: Alternative model specification–spatial Durbin error model with spatial and time-period specific effects.

	With spatial FE	With time-period FE	With two-way FE, bias corrected	SDM with two-way FE, bias corrected
ρ (spatial lag in TFP)				0.714397
				(0.000000)
γ_1 (patent stocks – K)	0.058261	0.106049	0.016941	0.011103
	(0.000217)	(0.000000)	(0.000397)	(0.020168)
β_1 (sec. educated – H)	0.068976	0.072004	−0.157716	
	(0.028574)	(0.019360)	(0.000000)	
γ_2 (spatial lag in K)	0.215392	0.139198	0.059737	0.031591
	(0.000000)	(0.000000)	(0.000000)	(0.093210)
β_2 (spatial lag in H)	0.430120	0.372689	−0.265759	−0.286826
	(0.000000)	(0.000000)	(0.000000)	(0.000000)
Spatial autocorrelation in the error term	0.190976	0.214994	0.205987	
	(0.000000)	(0.000000)	(0.000000)	
σ^2	0.0129	0.0352	0.0011	0.0011
Pseudo R^2	0.7376	0.8304	0.9948	0.9964
Adjusted R^2	0.1338	0.7743	0.2692	0.1311
LogL	2012.9104	594.73929	5487.1851	5433.6895

Notes: *p*-value in parentheses; pseudo R^2 represents a measure of the goodness of fit; adjusted R^2 includes punishment on the dimension of the model.

$$v_k = \frac{1}{D-1}\sum_{d=1}^{D}(\varphi_{kd} - \overline{\varphi}_k)^2 \tag{8b}$$

$$\tau = \frac{\overline{\varphi}_k}{\sqrt{\frac{1}{D-1}\sum_{d=1}^{D}(\varphi_{kd} - \overline{\varphi}_k)^2}} \tag{8c}$$

The focus of this paper is on the (*i*, *j*) th elements of the matrix of partial derivatives corresponding to the regions Vienna, Budapest and Bratislava in *T* subsequent years. Since we have two explanatory variables, we have two matrices of partial derivatives. Table 4 reports the mean and standard deviations of the impact metrics corresponding to the two explanatory variables following Eqs. (8a) and (8b).

We report the average annual direct (the first line of Table 7) and indirect (the upper half part of Table 3) effects and compare them with the total indirect effects (the last line of Table 7) and interregional spillovers of some other selected NUTS-2 regions located in the immediate neighborhood, namely Lower Austria (Niederösterreich), the Györ region (Nyugat-Dunántúl) and the Brno region (Jihovýchod). Table 7 shows that both domestic and foreign knowledge and human capital exhibit significant impacts on the TFP in the area. Domestic human capital appears to be slightly more important for TFP in Vienna than in the capital regions of Slovakia and Hungary. However, spillover effects from foreign human capital seem to be

Table 7
Estimated direct and indirect effects on TFP in the triangle of capital regions Vienna–Budapest–Bratislava compared to the effects on TFP in other close regions.

	K in Vienna	H in Vienna	K in Budapest	H in Budapest	K in Bratislava	H in Bratislava
Direct Effects	0.0783	0.0906	0.0795	0.0807	0.0793	0.0819
	(0.0028)	(0.0302)	(0.0026)	(0.0287)	(0.0027)	(0.0289)
Indirect Effects on Bratislava	0.0050	0.0245	0.0017	−0.0007	–	–
	(0.0005)	(0.0052)	(0.0005)	(0.0004)	–	–
Indirect Effects on Budapest	0.0011	0.0006	–	–	0.0013	0.0009
	(0.0001)	(0.0074)	–	–	(0.0005)	(0.0003)
Indirect Effects on Vienna	–	–	0.0048	0.0224	0.0069	0.0215
	–	–	(0.0001)	(0.0014)	(0.0004)	(0.0050)
Indirect effects on other close regions						
Indirect Effects on Brno region	0.0038	0.0278	0.0016	0.0017	0.0027	0.0175
	(0.0001)	(0.0074)	(0.0001)	(0.0003)	(0.0001)	(0.0046)
Indirect Effects on Lower Austria	0.0075	0.0953	0.0005	0.0028	0.0027	0.0040
	(0.0002)	(0.0279)	(0.0000)	(0.0009)	(0.0001)	(0.0012)
Indirect Effects on Gyor region	0.0016	0.0008	0.0037	0.0346	0.0027	0.0158
	(0.0001)	(0.0003)	(0.0002)	(0.0070)	(0.0001)	(0.0040)
Total Indirect Effects	0.1132	0.0350	0.0747	0.1020	0.0963	0.0032

Notes: standard deviations in parentheses; K denotes the stock of knowledge embodied in the EPO patent applications; H is share of working age population with at least secondary education (ISCED 3–6).

largest in magnitude in Budapest. In terms of patent stocks, the direct effects are quantitatively very similar in the three capital city regions under scrutiny.

The estimated values reported in Table 7 have interesting implications. First, Budapest proves to have a large R&D potential. It is the greatest beneficiary of human capital transfers within the area. The spillover effects from foreign human capital are even higher than the domestic contribution of human capital. This may be attributable to the growing participation of Budapest in international research networks. Through institutions such as the Central European University and the European Institute of Technology residing there, Budapest accesses international funding and attracts European human capital. Yet Vienna appears to be a less important partner in the knowledge transmission process than the other EU regions. This result might be attributable to some competition effect between the capital city regions.

Second, Vienna emerges as an important donor of knowledge in the surrounding area. Vienna's human capital helps Bratislava and the region in between–Lower Austria–to grow. Vienna's human capital also appears to be important for the TFP in the Brno region, but only does very little for the TFP in the Hungarian regions. On average, Bratislava receives fewer knowledge spillovers from EU regions as compared to Budapest or Vienna. This might explain why the estimated impact of Vienna's knowledge appears to be excessive–it is on average 7.57 times higher than the spillovers from any other EU region. The relatively small effects of average EU regional knowledge can be explained by the long-run emigration of skilled workers from Bratislava to other EU countries (Ivancheva and Gourova, 2011).

Third, the effects of interregional human capital between Bratislava and Vienna may be two-way. Bratislava's human capital is also relevant for Vienna's TFP. Since Slovakia's EU accession in 2004, mobility and cooperation between Vienna and Bratislava have boomed. In particular, a lot of skilled labor was attracted by the higher wages offered in Vienna. It is a common observation that skilled workers from Bratislava are employed, receive training and stay productive in Vienna while maintaining their permanent residence in Bratislava. In such cases, Bratislava's workforce also utilizes knowledge in Bratislava. The presence of feedback loops may further strengthen the responsiveness of TFP levels in Bratislava to human capital in Vienna. This evidence is the first of its kind and therefore we suggest viewing it as indicative and not conclusive. It should be extended to more empirical work, particularly micro-studies on mobility and particular channels of knowledge transfer among the selected regions.

In the current debate on the future of EU cohesion policy and regional efforts to grow and connect internationally, our conclusions may provide a guide to policymakers and their strategies. First of all, they can see that knowledge spillovers are still somewhat restricted between the Western and Eastern EU. Knowledge spillovers to Bratislava originate from Vienna, but not so much from other EU regions. The Budapest region seems to do better and attracts knowledge from other countries, but not from Vienna. This indicates that knowledge transfers in the EU might not be fully restricted to the closest cities and that other factors may impact geographically disadvantaged regions. Unfortunately, exploring these other factors goes beyond the scope of this paper. But the observation hints that the international connections of a region, resulting from renowned education or research facilities located there, matter.

The question emerges what can be done to improve the situation where other regions such as the Bratislava region basically depend on one single region in the neighborhood. Obviously, Vienna constantly appears at the top of R&D spending and patenting regions in the EU and the knowledge accumulated there may be viewed as sizeable, but depending on just one region makes the local productivity in Bratislava vulnerable. It would be advisable to diversify the cooperation ties of Bratislava to other R&D-intensive regions.

6. Concluding remarks

Using a knowledge production function, the paper estimates the contribution of knowledge and human capital stocks on total factor productivity in European sub-national regions. Since total factor productivity in European regions appears to exhibit strong spatial autocorrelation, we employ a spatial Durbin panel model for the period of 2000–2010 to explicitly account for spatial dependence in the dataset. Moreover, these spatial econometric frameworks allow for the quantification of spillover effects of knowledge and human capital stocks on total factor productivity.

Special emphasis is laid on the estimation of knowledge spillovers between Eastern and Western European regions. Based on its unique geographical closeness among European regions, an empirical illustration focuses on the triangle of capital city regions Vienna-Bratislava-Budapest. The empirical results show that the transmission of knowledge in the area–despite support from EU cohesion policy–is still somewhat restricted. Bratislava appears to be far more dependent on knowledge accumulated in Vienna than in other EU regions. To the contrary, Budapest's productivity seems more responsive to knowledge and human capital endowments from other EU regions than Vienna.

Acknowledgements

Our sincerest thanks go to Professor Manfred M. Fischer from the Vienna University of Economics and Business for his extensive support and most valuable comments throughout the preparation of this manuscript. We are also deeply grateful to Nicolas Debarsy from the University of Orleans and three anonymous referees for their most useful feedback, as well as Paul Elhorst for his help with the Matlab codes. Our thanks also go to Professor John Hudson from the University of Bath for proofreading. We also acknowledge financial support from OEaD (Action Slovakia-Austria) and VEGA No. 1/0277/14 (V-14-046-00) titled *Innovation and competitiveness of the Slovak economy*. The usual disclaimers apply.

References

Caballero, R.J., Jaffe, A.B., 1993. How high are the giants' shoulders: an empirical assessment of knowledge spillovers and creative destruction in a model of economic growth. NBER Macroecon. Ann. 8, 15–86.
Cuaresma, J.C., Feldkircher, M., 2013. Spatial filtering, model uncertainty and the speed of income convergence in Europe. J. Appl. Econometr. 28 (4), 720–741.
Cuaresma, J.C., Doppelhofer, G., Feldkircher, M., 2014. The determinants of economic growth in European regions. Reg. Stud. 48 (1), 44–67.
Easterly, W., Levine, R., 2001. It's not factor accumulation: stylized facts and growth models. World Bank Econ. Rev. 15 (2), 177–219.
Elhorst, J.P., 2012. Spatial Econometrics: From Cross-sectional Data to Spatial Panels. SpringerBriefs in Regional Science. Springer Heidelberg, New York Dordrecht London.
Ertur, C., Koch, W., 2007. Growth, technological interdependence and spatial externalities: theory and evidence. J. Appl. Econometr. 22.6, 1033–1062.
Fischer, M.M., Scherngell, T., Jansenberger, E., 2006. The geography of knowledge spillovers between high-technology firms in Europe: evidence from a spatial interaction modeling perspective. Geogr. Anal. 38 (3), 288–309.
Fischer, M.M., Scherngell, T., Reismann, M., 2009. Total factor productivity effects of interregional knowledge spillovers in manufacturing industries across Europe. Geogr. Anal. 41, 204–220.
Fischer, M.M., 2011. A spatial Mankiw-Romer-Weil model: theory and evidence. Ann. Reg. Sci. 47 (2), 419–436.
Görzig, B., 2007. Depreciation in EU Member States: Empirical and Methodological Differences. EU KLEMS Working Paper Series No 17. . (Available at:) http://www.euklems.net/pub/no17%28online%29.pdf.
Griliches, Z., 1979. R&D and the productivity slowdown. Am. Econ. Rev. 70, 343–348.
Griliches, Z., 1990. Patent statistics as economic indicators: A survey, J. Econ. Lit. 28, 1661–1707.
Hall, R.E., Jones, C.I., 1999. Why do some countries produce so much more output per worker than others? Q. J. Econ. 114 (1), 83–116.
Hernández, J.A., Mauleón, I., 2005. Econometric estimations of a variable rate of depreciation of the capital stock. Empirical Econ. 30, 575–595.
Ishise, H., Sawada, Y., 2009. Aggregate returns to social capital: estimates based on the augmented-solow model. J. Macroecon. 31 (3), 376–393.
Ivancheva, L., Gourova, E., 2011. Challenges for career and mobility of researchers in Europe. Sci. Public Policy 38 (3), 185–198.
Jerzmanowski, M., 2007. Total factor productivity differences: appropriate technology vs. efficiency. Eur. Econ. Rev. 51 (8), 2080–2110.
Jones, C.I., 1995. R&D-based models of economic growth. J. Polit. Econ. 103 (4), 759–784.
Jorgenson, D., Griliches, Z., 1967. The explanation of productivity change. Rev. Econ. Stud. 34 (99), 249–280.
Katayama, H., Lu, S., Tybout, J.R., 2009. Firm-level productivity studies: illusions and a solution. Int. J. Ind. Organiz. 27 (3), 403–413.
Klenow, P., Rodriguez-Clare, A., 1997. The neoclassical revival in growth economics: has it gone too far? NBER Macroeconomics Annual 1997. MIT Press, Cambridge, MA, pp. 73–103.
LeSage, J.P., Fischer, M.M., 2008. Spatial growth regressions: model specification, estimation and interpretation. Spatial Econ. Anal. 3 (3), 275–304.
LeSage, J.P., Pace, R.K., 2009. Introduction to Spatial Econometrics. CRC Press Taylor and Francis Group, Boca Raton.
Mankiw, N.G., Romer, D., Weil, D.N., 1992. A contribution to the empirics of economic growth. Q. J. Econ. 107, 407–437.
Oulton, N., Srinivasan, S., 2003. Capital Stocks, Capital Services, and Depreciation: and Integrated Framework. Working Paper No. 192. Bank of England, UK.
Prescott, E.C., 1997. Needed: a theory of total factor productivity. Int. Econ. Rev. 39 (3), 525–551.
Schultz, T., 1960. Capital formation by education. J. Polit. Econ. 68, 571.
Yu, J., Lee, L., 2010. Estimation of spatial autoregressive panel data models with fixed effects. J. Econometr. 154, 165–185.