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The impact of knowledge spillovers on regional total factor productivity. New empirical evidence from selected European countries

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Abstract

This paper aims to identify the contribution of knowledge capital and its determinant – human capital – to total factor productivity differences among regions within a regression framework in general and the impact of their spillovers on regional total factor productivity in particular. The focus is laid on interregional spillovers between the Western and Eastern EU and namely, within the triangle of capital regions Vienna-Budapest-Bratislava. The results challenge some previous empirical studies in the sense that once the human capital is accounted for, the significance and magnitude of spillovers from conventional reservoirs of knowledge – patent stocks – falls. Vienna appears to be the largest contributor to the productivity increases in Bratislava. Budapest's productivity seems to be sensitive to knowledge and human capital endowments of EU, but not those of Vienna.

Keywords: knowledge capital, knowledge spillover, human capital, human capital spillover, total factor productivity, spatial panel

JEL: O330, O470, R120

1 Introduction

Recent empirical literature on economic growth has shown that differences in income levels, both at country and regional levels, are mainly due to disparities in total factor productivity (TFP) (Klenow and Rodriguez-Clare, 1997; Easterly and Levine, 2001; Jerzmanowski, 2007). Several explanations for the TFP have been put forward, but knowledge capital appears to play a key role (Griliches, 1979), both domestic and foreign one (Jaffe, 1986). After 10 years in the EU, most post-communist economies experience acceleration of TFP while their own research and development (R&D) intensity stays intact. Some studies explain this TFP gap by knowledge spillovers through foreign trade and flows of capital (Keller, 2010; Krammer, 2014). But are there any spatial spillovers between the Western and the Eastern EU? If yes, how large are they? How large are they compared to the average spatial spillover effects in the EU?

This paper aims to address these and other pending questions and identifies the contribution of knowledge capital and its determinant – human capital – to total factor productivity differences among regions within a regression framework in general and the impact of their spillovers on regional total factor productivity in particular. The analysis is

extended to exploration of spillovers amongst Western and Eastern EU regions for what purpose the triangle of capital regions Bratislava, Vienna and Budapest, was picked. First, they represent the Western and Eastern part of the EU. Second, they differ in their domestic R&D intensity. Third, no other three capitals in the EU are so geographically close to each other. Due to wage disparities, growing number of Slovak workers is driven to work in Vienna. Budapest, on the other hand, might contribute to knowledge accumulation in the area since it has been gradually given international research attention. It was made an official seat of several research institutions which are funded internationally, such as European Institute of Technology (EIT) or Central European University. For all the reasons, we assume that this triangle of capitals has been experiencing particularly strong, if not the strongest, spatial knowledge spillover effects amongst the neighboring regions of Western and post-communist EU countries.

The remainder of the paper is organized as follows: in the next section, we provide some theoretical and empirical foundations for our study. In the third section, we introduce the theoretical model and its empirical specification. Further, we explain the sources and construction of the data. In the fifth section, we present the estimation results. Subsequently, we show the strength of spillover effects amongst the selected capital regions. Concluding remarks are summarized in the final section.

2 Theoretical and empirical foundations of knowledge spillovers

The concept of knowledge capital (Griliches, 1979) is rather complex. Any assets of intangible nature covering foremost skills, managerial and organizational know-how, patents, and efficient ways of work conduct can be considered to be part of knowledge capital. When employed in production, knowledge raises the efficiency of production factors. Since knowledge is of intangible nature, its creator is unable to fully restrict the others to access it and utilize it for their own benefit. Of course, some restrictions apply. Foremost, domestic productivity gains spurred by foreign knowledge capital may be collected in case a region is geographically close to some knowledge-capital-endowed regions (Fischer et al, 2009) or in case a region actively participates in international flows of goods, services, capital and labor with some knowledge-capital-endowed regions¹. The spatial knowledge diffusion is mostly viewed as non-pecuniary one while the international trade, capital and labor flows are often associated with pecuniary transfers what suggests knowledge transfers being proxied by those pecuniary terms. The primary focus of this paper is on the knowledge externalities of the second kind.

Up till recently, literature seemed to neglect the spatial knowledge spillovers. Even though studies at the national (Ford and Rork, 2011; Kemeny, 2010; Kose et al., 2009), inter-industry (Jordaan, 2008) and inter-company level (Barbosa and Eiriz, 2009) have been occasionally accompanied by exploration of knowledge externalities at the regional level

¹ Most literature focuses only on one channel of knowledge flows, for example trade (Ferreira and Trejos, 2011; Mendi, 2007) or foreign direct investments (FDI) (Woo, 2009; Bode et al., 2012). Few recent studies have addressed simultaneous effects of trade and FDI on TFP (Ang and Madsen, 2013; Krammer, 2014).

(Bottazzi and Peri, 2003), the significance of geo-factor emerged in this context only with the study of Fischer et al. (2009). The theoretical framework for the study was developed by Ertur and Koch (2007) who included spatial autocorrelation in the neoclassical and endogenous growth models. Fischer et al. (2009) conclude that knowledge externalities are present and significant. The elasticity of the regional TFP on foreign knowledge capital accounts for app. 0.1 meaning that 1 % increase in knowledge capital in neighboring regions spurs on average 0.1 % increase in domestic TFP. However, Fischer et al. (2009) consider the sample of Western EU regions spanning the period up till the EU enlargement in 2004. There is still very little known about spatial knowledge spillovers in the Eastern EU, not to mention the particular transfers between the Western and Eastern EU regions.² Moreover, no spatial attempt has been registered so far that would study knowledge spillovers through the lens of knowledge production function.

The knowledge production function (Jones, 1995) shows that production of any new knowledge is directly linked to the extent of previous knowledge and human capital available in the economy. The function implies that human capital has positive impact also to the TFP. However, the empirical literature is struggling to prove so. There is evidence that human capital contributes positively to the aggregate output (Ishise and Sawada, 2009; Mastromarco and Ghosh, 2009), but the link to the TFP appears in growth regressions often negative. The phenomenon is known as human capital growth puzzle. It can be addressed by the threshold theorem indicating that once human capital reaches certain threshold level, it does not matter for knowledge capital formation anymore (Romer, 1990). Furthermore, an econometric explanation in empirical transformation of covariances and inclusion of fixed effects (Arcand and d'Hombres, 2007), or exogeneity of human capital growth with respect to the efficiency levels (Mankiw et al., 1992) might be viewed as responsible. Alternatively, one can focus on R&D productivity, i.e. productivity of human capital within the knowledge production function (Abdih and Joutz, 2006).

Similarly to knowledge capital, human capital can also spur positive externalities across borders. The studies draw on some earlier micro work of Jovanovic and Rob (1989) and Acemoglu (1996) showing that the individual's productivity is increased by interacting with and learning from high skilled workers. Some other studies post evidence that human capital exerts positive externalities also on aggregate productivity (Moretti, 2004; Shapiro, 2006; Niehaus, 2012). Rosenthal and Strange (2008) demonstrate localization effects of such externalities. In context of knowledge capital generation, the reasons for such externalities might be twofold. First of all, human capital is a carrier of important non-patentable knowledge such as efficient work of conduct or managerial skills. Second of all, knowledge generation process is no more a matter of just one company or region. The R&D agents are willing to cross borders and engage human capital from other regions. Availability of human capital in (geographic or economic) neighborhood is there preferred as rising distance increases transmission costs, as well as risk of knowledge distortion.

² By Western countries we mean the pre-2004 EU countries. The countries that accessed the EU in May 2004 and 2007 are in this paper referred to as the Eastern EU.

3 Model

Denoting regions by $i= 1, \dots, N$ and time periods by $t= 1, \dots, T$, Jones (1995) says the knowledge capital K_{it} is produced in a function of human capital H_{it} with some productivity δ called the R&D productivity:

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

ΔK_{it} denotes output of the process – the knowledge accrual and K_{it-1} stock of knowledge available at the beginning of the time period. $\exp(\omega_{it})$ stands for the error term. β and γ are elasticities of new knowledge generated with respect to human capital and already available knowledge stock.

Both inputs into the knowledge production function are often put directly into the Cobb-Douglas production function where they are considered to increase the efficiency of the production factors or to shift the technology frontier (Jerzmanowski, 2007). The modified Cobb-Douglas function reads then as:

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

where Y_{it} denotes the output, L_{it} labor, C_{it} physical capital, K_{it} knowledge capital and H_{it} human capital. The exponential error term ε_{it} reflects all uncaptured factors of output and productivity and is assumed to be identically and independently distributed with mean zero and standard deviation σ^2 . α , $1-\alpha$, γ a β are the output elasticities with respect to labor, physical capital, knowledge and human capital.

Following endogenous growth models, we put knowledge stock K_{it}^{γ} equal to the combination of intra-regional knowledge $K_{it}^{\gamma_1}$ and extra-regional knowledge $K_{jt}^{\gamma_2}$. Similarly, positive effects of human capital H_{it}^{β} are not to be attributed solely to intra-regional knowledge $H_{it}^{\beta_1}$ but also to the sum of extra-regional human capital $H_{jt}^{\beta_2}$. Calculating TFP in the usual way as $F_{it} = Y_{it}/L_{it}^{\alpha} C_{it}^{1-\alpha}$ we arrive at the following theoretical model:

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

where δ_{it} is the productivity interference being the R&D productivity at home and abroad. The productivity interference indicates that the impact of human capital is positive only if the regions share the same human capital growth path. If the growth of skills is either positive or negative the impact of human capital turns out positive. In reality, such synchronization of R&D productivities is rare – especially given a sample of large N and T . This interference may then contribute to instability of human capital in the growth regressions.

In accordance with the spatial point of view, the spillovers from a region i to a region j are conditional on some closeness (neighborhood). The closeness can be geographical (for example, k -nearest neighbors) or economic (for example, top trade partners), but the latter is

less preferred as it introduces endogeneity into the estimates. The neighborhood of regions i and j is captured in a spatial weight matrix W_{ij} where each (i, j) th element is 1 if and only if the region j is considered a neighbor, and 0 otherwise. In this context, we denote extra-regional knowledge $K_{it}^{\gamma_2}$ and human $H_{it}^{\beta_2}$ capital stocks as follows:

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

$$H_{it}^{\beta_2} = \left[\sum_{j \neq i}^N W_{ij} H_{jt} \right]^{\beta_2} \quad (5)$$

where $i, j \in N$ and K_{jt} and H_{jt} stand for knowledge and human capital stock of region j at time t , respectively. The knowledge and human capital at time t is conducive to both domestic as well as neighboring productivity changes.

Current literature disposes of rather weak proxies for human capital and knowledge capital. Knowledge capital is often represented by stocks of patent applications and human capital by tertiary educated population. 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 administration burden associated with a patent registration, or the conditions for a patent application are simply not met (general applicability in practice, providing a new solution). As an example of a non-patentable innovation we can think of an own organizational setting or a successful motivation technique. Even though it increases labor productivity, it is often context-related and the innovator feels less driven to protect it. Besides, many patents are just upgrades of already existing patents and as such they may increase productivity less than a single patent of revolutionary nature. In other words, the productivity accrual for different patent applications varies considerably.

New knowledge may have also less to do with the share of tertiary educated population in an economy what is a standard proxy of human capital in an economy. Share of people holding a university degree may provide some insight into the capabilities of a region to be efficient at work considering that the longer a person is educated, the longer he/she is forced to train the brain, polish the skills and gain new knowledge. There is, however, weak evidence that holding a tertiary degree secures that a person innovates more or that his/her productivity increases. Partially it is imputable also to the quality of education a graduate has received. According to various rankings (such as Academic Ranking of World Universities), universities from the post-Communist EU countries lag significantly behind the Western universities who publish more in scientific journals, get more cited, patent more and are more involved in international research.

The quality of education, skills acquired outside academia, as well as non-patentable knowledge are just few examples of omitted variables which arise in our model due to imperfect proxies available for explanatory variables. Following Ertur and Koch (2007), these

omitted variables are presumably also spatially correlated and thus, appear in our model as the spatial lag in either the error term (Spatial Durbin Error Model (SDEM) specification) or in the endogenous variable (Spatial Durbin Model (SDM) specification). We assume that all the omitted variables are endogenous to knowledge capital as they are to the TFP and that the SDM specification may then be more appropriate. Therefore, we introduce the spatial autocorrelation term in TFP $-\sum_{j \neq i}^N W_{ij} \ln F_{jt}$ with the parameter ρ .

Apart from the knowledge generation process, we assume that there are significant disparities amongst the EU regions in terms of their background and temporal factors. The space-specific time-invariant variables could be, for example, climate, the access to sea, presence of large cities, cultural and national traditions, norms and habits. The most common spatial-invariant variables abound changes in legislation or crisis break-out. Failing to account for these variables increases the risk of obtaining biased estimation results (Elhorst, 2012).

Taking into account all these empirical assumptions and taking logs, we rewrite the theoretical model from Eq. (3) as follows:

$$\begin{aligned} \ln F_{it} = & \rho \left[\sum_{j \neq i}^N W_{ij} \ln F_{jt} \right] + \beta_1 \ln H_{it} + \gamma_1 \ln K_{it} + \beta_2 \left[\sum_{j \neq i}^N W_{ij} \ln H_{jt} \right] + \\ & + \gamma_2 \left[\sum_{j \neq i}^N W_{ij} \ln K_{jt-m} \right] + \mu_{it} + \zeta_{it} + \varepsilon_{it} \end{aligned} \quad (6)$$

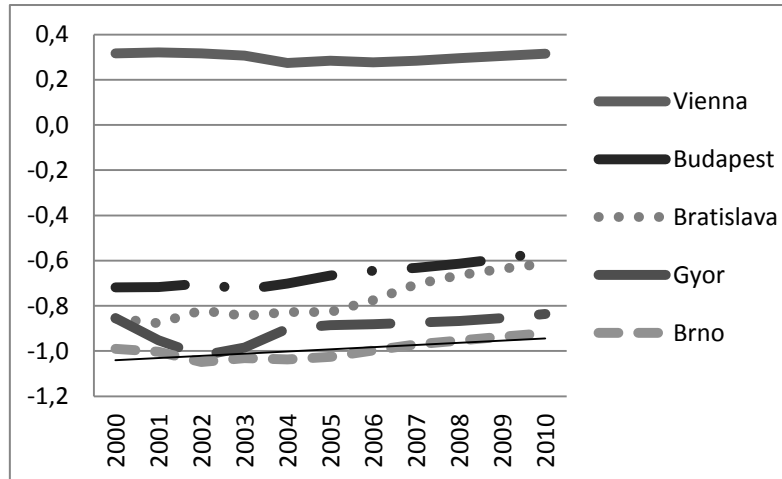
where spatial fixed effects μ_{it} account for spatial time-invariant heterogeneity among regions and spatial time-period fixed effects ζ_{it} take out impact of various temporal disturbances.

4 Data

In order to construct the TFP data, we follow robust calculus of Fischer et al. (2009). As mentioned in the previous section, we define total factor productivity F in the usual way as $\ln F_{it} = \ln Y_{it} - s_{it} \ln L_{it} - (1 - s_{it}) \ln C_{it}$ and use gross value added data in Euro (constant prices of 2000, deflated) as measure of output Y_{it} , s_{it} denotes the NT -by-1 vector of regional shares in production costs, and contains cost-based factor shares that are robust in the presence of imperfect factor shares. The calculus is as follows: wage remunerations divided by sum of wage remunerations plus investments. L_{it} stands for regional labor and C_{it} for physical capital. The stocks of physical capital are derived from gross investments I_{it} in current prices using the perpetual inventory method. The initial capital stock C_{it} was calculated based on data for 1990-1999 with depreciation rate $r=0.12$ (Fischer et al., 2009) and each subsequent stock of physical capital follows the calculus $C_{it+1} = C_{it} (1-r) + I_{it+1}$. All the data (gross value added, wage remunerations, investments, labor, hours worked) was taken from Cambridge Econometrics. The data on labor inputs was adjusted by hours worked.

The Figure 1 demonstrates the TFP levels for selected regions between the Eastern and Western EU. In accordance with our assumptions, Bratislava and Budapest do catch up in terms of TFP with Vienna. The catch-up accelerated after the EU accession of Slovakia and Hungary in 2004. The convergence of Brno and Gyor (regions of other large Eastern EU cities in the Vienna neighborhood) is less tractable. The significance of knowledge and human capital spillovers for this TFP catch up will be scrutinized in the section 5.

Figure 1. Trajectory of $\ln(\text{TFP})$ in the selected regions



Source: own calculations, data from Cambridge Econometrics

In order to proxy knowledge capital, we use patent stocks calculated from patent applications to the European Patent Office (EPO) using again the perpetual inventory method. Thus, the patent stocks per region i at the end of period $(t+1)$ is denoted as $K_{it+1} = K_{it} (1-r) + P_{it+1}$ 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 the knowledge embodied in EPO patent applications. The number of EPO patent applications was taken from Eurostat Regional Databases. Greek regions were excluded because of data scarcity. The depreciation rate $r=0.12$ was taken following the study of Caballero and Jaffe (1993).

As a proxy of human capital H , we employ share of population aged 25-64 with low education attainment (completed ISCED 1-2 level). We decided to do so because as mentioned earlier in the text, other human capital proxies (such as tertiary educated population share or number of schooling years) do perform confusingly in growth regressions. When searching for an alternative proxy for human capital, it makes sense to assume that a person may gain skills and increase productivity unless he/she has received too little education. How much exactly is “too little” may vary across research studies. In this paper, we assume that these skills are comparable to secondary education (ISCED level 1-2). The data on share of low educated population was taken again from Eurostat Regional Databases.

We denote each element of the spatial weight matrix w_{ij} and put $w_{ij} = d_{ij}^{-1}$ assuming an inverse power relationship where d_{ij} denotes circle distance between the region i and region j . The distance d_{ij} is measured as distance between the i 's centroid and the j 's centroid. The longitude and latitude of each region was taken from GISCO Eurostat database. The longitude and latitude of each region's centroids were determined using ArcGis. The spatial weight matrix was row-standardized so that overestimation problems are avoided (Elhorst,

2012). Our spatial weight matrix specification implies that spatial spillovers of region-external knowledge capital influence all other regions, but the spillover effects are subject to a spatial decay. As we assume non-zero spatial weight matrix, we assume global effects from both explanatory variables. The global effects from the TFP are secured through the Jacobian term $(I-\rho W)^{-1}$.

5 Spatial panel estimation

We organized our data into a spatial panel. Spatial panels contain typically time series observations over a number of geographical units. In our case, we consider $N=251$ NUTS-2 regions and $T=11$ years. We estimate an SDM model with both spatial and time-period fixed effects as demonstrated by the Eq. (6) using the software developed by Paul Elhorst and downloadable at <http://www.regroningen.nl/elhorst/software.shtml>. The software was developed based on theoretical foundations of Yu and Lee (2010). First, it creates dummies for each region and each year, demeanes the dependent and explanatory variables, and then estimates the demeaned values by maximum likelihood (MLE). Since the model accounts for both spatial and time-period fixed effects, the demeaning procedure biases the estimates and we need to employ the bias-corrected version of the concentrated log-likelihood function L. Elhorst package requires the panel to be balanced.

Table 1. Estimation results: spatial Durbin model specification with spatial and time-period specific effects, bias corrected

Determinants	SDM spatial and time-period fixed effects, bias corrected, distance decay	
ρ (spatial lag in TFP)	0.892652	(0.000000)
γ_1 (patent stocks - K)	0.015319	(0.002318)
β_1 (low educated - H)	0.015790	(0.138792)
γ_2 (spatial lag in K)	0.007829	(0.418628)
β_2 (spatial lag in H)	-0.174730	(0.000000)
σ^2	0.0013	
R^2	0.9960	
corrected R^2	0.0663	
logL	5307.969	
Wald test spatial lag	50.7490	(0.0000)
LR test spatial lag	60.4087	(0.0000)
Wald test spatial error	69.2326	(0.0000)
LR test spatial error	84.6826	(0.0000)

Note: p-value in parentheses, corrected R^2 is R^2 without the contribution of fixed effects, df=degrees of freedom

Table 1 shows results of the spatial panel model estimation for the parameters ρ , β_1 , β_2 , γ_1 , γ_2 related to spatial lag in TFP, to human and knowledge capital and their spatial lags, respectively. The results demonstrate strong autocorrelation in the dependent variable TFP. Both the Likelihood Ratio (LR) and Wald tests point out that the spatial lags in the exogenous variables shall not be omitted in favor of a spatial lag model. Besides, lower values of the

Wald and LR tests by SDM than by SDEM indicate that the SDM model is probably more appropriate for our data than the SDEM model. The strong autocorrelation in the TFP may be imputable to weakness of knowledge capital proxies and inertia effects.

Following LeSage and Pace (2009), the point estimates and their t-values often lead to erroneous conclusions if the spillover effects exist or not. The reason is that if the patent stock in region i changes, not only the TFP in that region changes (direct effect γ_1), but also the TFP in neighboring regions (indirect effect γ_2). The partial derivatives of the expected elasticity of TFP with respect to patent stocks K in a region 1 till N in time can then be shown as:

$$\left[\frac{\partial E(F)}{\partial K_1} \dots \frac{\partial E(F)}{\partial K_N} \right] = (I - \rho W)^{-1} \begin{bmatrix} \gamma_1 & w_{12}\gamma_2 & \dots & w_{1N}\gamma_2 \\ w_{21}\gamma_2 & \gamma_1 & \dots & w_{2N}\gamma_2 \\ \dots & \dots & \dots & \dots \\ w_{N1}\gamma_2 & w_{N2}\gamma_2 & \dots & \gamma_1 \end{bmatrix} \quad (7)$$

where w_{ij} is the (i,j) th element of the spatial weight matrix W . Instead of point estimates, LeSage and Pace (2009) suggest to report one summary indicator for the indirect (spillover) effects, measured by the average of either the row sums or the columns sums of the off-diagonal elements of the matrix and one summery indicator for direct effects, represented by the average of diagonal elements of the matrix. In compliance with this approach, we estimate the average effects – Table 2.

Table 2. Direct and indirect effects estimates based on the coefficient estimates of the spatial Durbin model with spatial and time-period fixed effects, bias corrected, as reported in Table 1

Determinants	Patent stocks (P)		Low educated population (H)	
Direct Effects	0.018944	(0.000111)	-0.011330	(0.315048)
Indirect Effects	0.196603	(0.008475)	-1.491739	(0.000000)
Total Effects	0.215547	(0.004112)	-1.503069	(0.000000)

Note: p-value in parentheses

Table 2 demonstrates the disparity in TFP elasticities on our proxies of knowledge and human capital. The elasticity of TFP on domestic patent stocks appears positive and significant. The indirect (spillover) effects from patent stocks appear positive, but slightly insignificant (significance below 10 % level). The low-skilled population is strongly insignificant for domestic TFP levels, but spillover effects from lack of skilled population in the neighboring regions emerge strongly significant and considerably larger in magnitude than effects (direct and indirect) from patent stocks. If the low education population increases by 1% in all regions except one, the domestic TFP will decrease on average by 1.503 %.

These results seem to find justification in empirical reality. Even though our results are not able to answer the question if the productivity gains are imputable to cross-border search of R&D agents for skills and/or transmission of non-patentable knowledge, we detect strong

responsiveness of TFP levels to human capital scarcity across the EU regions. The effects from conventional knowledge reservoirs – patent stocks – are mostly direct. The weak indirect effects from patent stocks might be hampered by the fact that in order to utilize patented knowledge foreign regions should often pay royalties to the patent owners. Moreover, a weak direct link of the patent stocks to the TFP may indicate presence of diminishing returns to R&D scale (Jones, 1995). With more knowledge available, the duplicity work rises, new patent applications are more and more often just upgrades of the already existing ones and thus, the productivity response to new patent applications is vanishing.

Our results were exposed to several robustness checks. First, following Katayama et al. (2009) we challenged the TFP calculus in terms of the depreciation rate of physical capital. We re-estimated the model for the 5.5 % rate as suggested for EU in 1990-2005 by Görzig (2007) and Hernández and Mauleón (2005) and for the 8 % rate following the results of Oulton and Srinivasan (2003). Second, we reproduced the estimations for various specifications of spatial weight matrix, namely for 4-, 6- and 8-nearest neighbors. To sum up, our estimates survived all these robustness checks and the details can be obtained upon request.

6 Focus on interregional spillovers in the capital regions of Bratislava-Vienna-Budapest

As already discussed in the previous section, the spillover (indirect) effects between two different regions in time correspond to a particular off-diagonal element of the impact matrix in time. Each diagonal element of the impact matrix denotes direct effects on one region resulting from the explanatory variable. The impact matrix exists for each explanatory variable. Transferring this into our case, the impact matrix of expected TFP responses to patent stock changes is demonstrated by the Eq. (7).

Based on the fact that we used MLE for our estimations, each (i, j) th (indirect effect) and (i, i) th (direct effect) element of the estimated impact matrix corresponds to the mean value drawn from the normal distribution with mean zero and standard deviation one. If we draw D parameters like this, the average (direct or indirect) effects can be approximated by the mean value over these D draws and its significance level (t-value) by dividing this mean by the corresponding standard deviation. If we take φ_{kd} as the effect of the k -th explanatory variable of draw d , the effect over all draws, its standard deviation s_k and the corresponding t-value τ will be

$$\bar{\varphi}_k = \frac{1}{D} \sum_{d=1}^D \varphi_{kd} \quad (9a)$$

$$s_k = \frac{1}{D-1} \sum_{d=1}^D (\varphi_{kd} - \bar{\varphi}_k)^2 \quad (9b)$$

$$\tau = \bar{\varphi}_k / \sqrt{\frac{1}{D-1} \sum_{d=1}^D (\varphi_{kd} - \bar{\varphi}_k)^2} \quad (9c)$$

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. As we have two explanatory variables, we have two matrices of partial derivatives – one for patent stocks and another one for the share of low educated population. Table 3 reports the mean values and standard deviations retrieved for both explanatory variables following Eq. (9a) and Eq. (9b).

Table 3. Estimated direct and indirect effects on TFP in triangle of capital regions Vienna – Budapest – Bratislava compared to the effects on TFP in other close regions

	P in Vienna	H in Vienna	P in Budapest	H in Budapest	P in Bratislava	H in Bratislava
Direct Effects	0.0146 (0.0049)	-0.0326 (0.0106)	0.0150 (0.0046)	-0.0231 (0.0099)	0.0149 (0.0047)	-0.0243 (0.0100)
Indirect Effects on Bratislava	0.0010 (0.0003)	-0.0172 (0.0026)	0.0003 (0.0001)	-0.0005 (0.0001)	---	---
Indirect Effects on Budapest	0.0002 (0.0001)	0.0002 (0.0026)	---	---	0.0003 (0.0001)	-0.0009 (0.0003)
Indirect Effects on Vienna	---	---	0.0002 (0.0001)	0.0013 (0.0014)	0.0010 (0.0003)	-0.0136 (0.0022)
Indirect effects on other close regions						
Indirect Effects on Brno region	0.0007 (0.0002)	-0.0100 (0.0026)	0.0003 (0.0001)	-0.0005 (0.0001)	0.0005 (0.0002)	-0.0052 (0.0016)
Indirect Effects on Lower Austria	0.0014 (0.0004)	-0.0343 (0.0098)	0.0001 (0.0000)	0.0008 (0.0003)	0.0005 (0.0002)	-0.0012 (0.0004)
Indirect Effects on Győr region	0.0003 (0.0001)	-0.0003 (0.0001)	0.0007 (0.0003)	-0.0099 (0.0024)	0.0005 (0.0002)	-0.0047 (0.0014)
Total Indirect Effects	0.0211	-0.0126	0.0141	-0.0292	0.0181	-0.0023

Note: standard deviations in parentheses, P denotes stock of knowledge embodied in the EPO patent applications, H stands for share of low educated population

In order to demonstrate how large role, in fact, the internal and external knowledge plays for TFP in the capital triangle area of Budapest-Bratislava-Vienna, we report average annual direct (the first line of Table 3) and indirect (the upper half part of Table 3) effects, and compare them with total indirect effects (the last line of Table 3) and interregional spillovers with some other selected NUTS-2 regions spreading in-between (such as Lower Austria - Niederösterreich and Győr region - Nyugat-Dunántúl) or in some neighborhood (Brno region - Jihovýchod). Following Table 3, both domestic and foreign knowledge capital abundance and human capital scarcity are significant for the TFP in the area. Domestic human capital seems to be slightly more important for TFP in Vienna than in the capitals of Slovakia and Hungary. However, the spillover effects from foreign human capital seem to be largest in

Budapest. In terms of patent stocks, the direct effects are magnitude-alike in all the three capitals while the larger sensitivity to foreign stocks of knowledge is recorded for Vienna.

The estimated values as reported in Table 3 do find empirical justification. Firstly, Budapest proves to have 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. That may be imputable to the growing participation of Budapest in international research networks. With the institutions such as Central European University and European Institute of Technology residing here, Budapest accesses international funding and invites international human capital from more distant EU regions than those considered in Table 3. That explains also the weak human capital spillovers from Bratislava or Vienna on Budapest relative to the total spillover effects.

Secondly, Vienna emerges as an important donor of knowledge in the area, particularly in terms of human capital. In particular, Vienna's human capital helps Bratislava and the region lying in-between – the Lower Austria - to grow. Vienna's human capital appears also important for Brno region, but only very little for the Hungarian regions. Bratislava receives fewer knowledge spillovers than Budapest or Vienna so the impact of Vienna's knowledge pops up excessive – it is 7.57-times higher than the spillovers from an average EU region. The relatively small effects of average EU-regional knowledge can be explained by the long-run negative balance of Bratislava in terms of tertiary educated migration.

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 the EU accession in 2004, the mobility and cooperation between Vienna and Bratislava has boomed. Especially a lot of high skilled labor got attracted by higher wages offered in Vienna. It is a common observation that Bratislava skilled workers get employed, receive training and stay productive in Vienna while maintaining their permanent residence in Bratislava. In such a case, Bratislava's workforce utilizes knowledge also back at home. The presence of feedback loops may further strengthen responsiveness of TFP levels to human capital. This evidence is first-of-its-kind and thus, we suggest viewing it as indicative and not conclusive. It shall be extended to some more empirical work, particularly micro-studies on the mobility and channeling of knowledge amongst the selected regions.

7 Concluding remarks

In this paper, we have estimated direct and spillover effects on total factor productivity levels induced by regional knowledge capital using the sample of both Eastern and Western 251 NUTS-2 EU regions in the period of 2000 till 2010. In contrast to previous studies, we approached knowledge capital through the lens of knowledge production function and employed latest techniques for spatial panel estimations. Our results detect some responsiveness of TFP to knowledge capital abundance and strong responsiveness to human capital scarcity across the EU regions. In particular we find that once the human capital is accounted for, the significance and magnitude of spillovers from conventional reservoirs of

knowledge - patent stocks – falls. That is a challenging result compared to the previous studies (Fischer et al, 2009) which focused only on patent stock externalities.

Logical explanation can be found for these findings. Human capital is the first and ultimate carrier of knowledge and not just of its patentable, but also of its various non-patentable kinds. With cross-border search for R&D partnership and rising mobility of talent, the spillover effects from human capital gain on significance and magnitude. The small TFP responsiveness to domestic patent stocks is consistent with the decreasing returns to R&D scale in the EU. With more knowledge available, the duplicity work rises and new patent applications are often only upgrades of already existing ones. On the other hand, the cross-border effects from patent stocks are hampered by royalties paid by patent users to the owners.

Our results also show strong spatial autocorrelation in the TFP. This is something most probably imputable to inertia effects and weakness of knowledge and human capital proxies we employed in this study. Even though empirical estimations and robustness checks look encouraging, we have to keep in mind that human and knowledge capital are studied in this paper only with proxies. There is objectively large pool of skills and knowledge effectively increasing the TFP levels which were excluded from our estimations. Periodicity in statistical surveys such as OECD's *Programme for the International Assessment of Adult Competencies* (PIAAC) may help research literature to address the role of human and knowledge capital for productivity levels more accurately.

The novelty of our paper lays also in the fact that we attempted to methodologically approach and report the knowledge spillovers between the Eastern and Western EU countries. For that purpose, we selected a triangle of capital regions which based on its unique geographical closeness amongst EU regions might be subject to intensive spatial knowledge spillovers – Budapest-Bratislava-Vienna. The TFP data indicates the same. Since Slovakia and Hungary accessed the EU, it shows clear catch-up of Bratislava and Budapest to the levels of Vienna. That does not accord with their persistently lagging levels of R&D spending and patenting.

The estimations confirmed our assumptions and uncovered what may stay behind. Firstly, Vienna's impact on Bratislava surpasses by far the TFP gains of Bratislava from an average EU region. However, it is not patent stock what stands behind. Vienna's human capital spillovers account for 7.57-times larger effects than the spillovers from an average EU region. That accords with the strong mobility between Bratislava and Vienna. Since EU enlargement in 2004 Bratislava's human capital got attracted to high-income Vienna and the geographical closeness makes it easier for human capital to get education or training, travel every day for work to Vienna and transfer knowledge and skills back to Bratislava. Secondly, Budapest reports large TFP gains from human capital spillovers in the EU but they are not attributable to the human capital in Vienna or Bratislava. That accords with the growing participation of Budapest in international research networks which serve as vehicles for knowledge transfers. The spatial effects of Vienna's human capital and patent stocks are not limited only to Bratislava although Bratislava is the largest beneficiary. Lower Austria and the Brno region also collect large TFP gains from Vienna's knowledge and skill endowments.

Our study is the first attempt to assess spatial spillovers between the Eastern and Western EU regions and to report how much the closeness of knowledge-intensive Vienna impacts TFP trajectory in Bratislava and Budapest regions. However, we have to keep in mind that we use only weak proxies of human and knowledge capital. Moreover, our construction of the spatial weight matrix is static and does not account for time lags in transmitting the knowledge. We decided to relax on knowledge spillovers impacts across years as with high mobility of human capital we assume that one year is relatively long time to transfer knowledge anyway. One may question our research setting suggesting some spatial time series analysis. However, the data scarcity prevents us to do so. Furthermore, our estimations indicate that there is quite large transfer of skills what can be further extended to more micro-setting and primary data collection.

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