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Symposium Article

Total Factor Productivity, Health and Spatial Dependence in Some European Regions

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This paper assesses the determinants of total factor productivities in 96 regions of EU15 and 27 regions of CEE, during 1999–2010 by considering R&D, human capital and infrastructure in a dynamic specification. We distinguish between private and public R&D and we consider the health component of human capital instead of the educational one, while estimating different models for the regions in EU15 and CEE. Although our main results point out that R&D is an important determinant of regional productivities in both EU15 and CEE, we find evidence solely for a strong public R&D impact on the productivities in the EU15 regions, robust to spatial dependence and different time frames. Health also has a positive impact on productivities, although its effect is less strong after the 2004 EU enlargement; while in the CEE regions, infrastructure appears to have a stable effect. Also, a conditional catch-up process to region-specific steady states seems to emerge in both EU15 and CEE regions.
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INTRODUCTION

The acceleration of the European Union (EU) integration process not only brought along the benefits that come with an enlarged common economic market, but has also enhanced the existing disparities between the European regions. These disparities, although more pronounced in the new member states, are an ongoing concern for all EU members. This is why the main objective of the regional policy of EU is to reduce disparities within European Community and encourage the development and convergence at the regional level. Also, the policy mix at the Community level aims to stimulate competitiveness and boost productivity growth especially through innovation. The Lisbon Strategy, followed by the 2020 Agenda, promotes a sustainable growth model that is based on productivity growth and innovation, while also advocating for social inclusion, increases in human capital and greater concern for the environment. In this context, the role of the regions as important units for research, innovation and social cohesion has already been acknowledged (European Commission, 2001). Therefore, finding means to encourage economic growth at a regional level can help reduce regional disparities while also boosting competitiveness for the whole Community.

For this purpose, we employ the concept of Total Factor Productivity (TFP). TFP is the main driver of economic growth in most mature economies, and understanding its determinants is essential in devising policies that help enhance growth prospects and competitiveness. The economic growth literature has shown theoretically and empirically the importance of the Solow residual (TFP) over factor accumulation. As a result, TFP which is mainly determined by technological progress is the main determinant of the performance of a country over time and also seems to account for the much of the differences in income levels and the growth rates.

The recent literature also looks for additional determinants of growth beyond the basic factors of production. A majority of these growth empirics treat the determinants of output growth as inputs, introducing them into the production function. However, these factors may affect output growth indirectly, by affecting their efficiency through an impact on production factors; this is the approach followed here.

When it comes to TFP determinants, endogenous growth theory establishes the role of innovative factors, such as R&D and human capital, as important determinants of TFP formation, also recognising that there are other factors that may lead to innovation and efficiency improvements. In addition, the empirical literature suggests that technological diffusion matters and thus, countries with low initial levels of productivity can benefit from research and development expenditures.

Even when it comes to these well-established determinants of TFP, empirical studies seem to consider only one aspect, human capital is usually proxied by education, and the health component is left aside. However, health has been recognised as an important factor in growth dating back to Grossman (1972) who modelled optimal investment in increasing longevity. Generally speaking, improved health increases the quality of the workforce, enhancing productivity and improving knowledge absorption. Although a majority of studies focus on the health-growth relationship in the underdeveloped countries, there are some arguments that the health variable is also relevant in the context of developed or developing economies. Tompa (2002) thinks that there are three channels through which health impacts productivity: a healthy person has a higher life expectancy, so she is keen to invest more in education, to save more over the years encouraging capital accumulation and to have more labour force participation. Also, the overall health status of the population, as is the case with education, might attract or discourage investments, especially FDI.

The role of infrastructure in stimulating output, efficiency and productivity growth and also reducing production costs has been considered in several empirical studies, since it draws the attention of policy makers all over Europe. In the theoretical literature, infrastructure is an important factor that can generate positive external economies (see Romer (1986), Lucas (1988), and Barro and Sala-i-Martin (1995)).

At the regional level, a labour force characterised by a high level of human capital represents an advantage for the firms which could enhance local productivity. The local economy benefits from healthy, educated employees who attract foreign direct investors to implement innovative activities inside the countries and thus, in fact, enhances productivity for the whole economy. For regional TFP, we think that R&D is important, since all regional firms may benefit from public R&D and also from their own private R&D expenses. Recently, the interest of theoreticians and practitioners from all over the world has increased in what concerns the role of human capital in developing the competitiveness of economies and, in particular, that of the regions.

Our paper brings additional evidence that human capital measured by health has a positive influence on TFP growth at a regional level. We also find evidence of R&D impact on regional productivity, especially of public R&D in the developed EU15 regions. We find no evidence of a significant private R&D effect; however, we argue that private innovative activity is larger than what it is actually measured by private R&D. Also, we share the opinion that the impact of public R&D is reflected across the entire economy including the private sector. This represents a good incentive for supporting further investment in the health aspect of human capital and also in the public innovation system. We also find evidence of an infrastructure effect on TFP, although this relation is more stable in the regions of Central and Eastern Europe (CEE) than in EU15.

The spatial dimension of regional analysis has also been discussed in the context of competitive clusters (Porter, 2003) and spatial spillovers (see Capello (2009) for a review on the matter). Innovation and productivity tend to be 'clustered' in some specific areas more than in others, but it could also be the case that productivity in one region can be influenced by those of neighbouring regions. We show that spatial conglomeration from capital cities matters for TFP creation and R&D activity, especially in the EU15 regions. Moreover, most of our results are robust when we control for the impact of neighbouring regions' productivity, proving that our estimated effect of the TFP determinants is not influenced by productivity spillover effects.

This paper is one of the few studies that attempts to study and compare TFP determinants for both, EU15 and Central and Eastern Europe (CEE) by considering R&D, health as a measure for human capital and public infrastructure. Although there is a general consensus that regions from newly acceded member states need to boost their productivity and become more competitive, most of the studies (discussed in the literature section) focus on the regions from developed EU countries.

In our estimations, we use the levels of TFP computed from a Cobb–Douglas production function with set input shares as the dependent variable and we express all variables in logarithmic transformations. We distinguish between public and private (business) R&D, as it is known that the two can affect productivity in different ways and we employ a novel variable that measures health: the number of doctors per working age population. We use 123 NUTS regions, out of which 96 belong to EU15 and 27 belong to CEE countries. Since EU15 and CEE regions have different characteristics based on their economic conditions and history, as well as differences in the length of their membership in the Common Market, we assume they are characterised by different production functions, so we present separate estimates for EU15 and CEE regions. The time frame used is 1999–2010. In order to deal with endogeneity and the dynamic character of the growth process, system GMM is used for estimations.

The paper is organised as follows: the first section reviews the literature on determinants of TFP, the next section discusses the European Union regions analysed, the following section deals with the data, variables and methodology, followed by a section that presents the results and, finally, the conclusions.

LITERATURE REVIEW OF REGIONAL TFP DETERMINANTS

For the EU area, the growth accounting studies emphasise the importance of TFP both in the western EU countries, considered to be developed, and also in the recently added 11 CEE countries. Musso and Westermann (2005) show that in Euro Area countries, the single most important contributor to real GDP growth over 1980–2003 was TFP. Schadler *et al.* (2006) emphasise the importance of TFP to growth in CEE countries during 1990–2004, stating that this large contribution of TFP is what separates this group of countries from other emerging economies.

The studies that assess the impact of TFP determinants in the EU regions focus mostly on the NUTS2 regions of the EU15 member states. Ladu (2010) provides TFP estimates for 115 European regions over the period 1976–2000, by using panel data cointegration techniques. Results show that some regions of France and Austria have the highest productivity, while the lowest TFP belongs to regions from Greece and Spain. Bronzini and Piselli (2009) estimate the determinants of TFP for the Italian regions over 1980–2001, by considering R&D, human capital and public infrastructure. Their causality tests reveal that there exists a long-run relationship between productivity level and the three variables, the strongest relationship being between human capital and TFP. Dettori *et al.* (2012) study the role played by intangible factors on TFP creation, by analysing three types of capital: human capital, social capital and technological capital, proxied by number of patents. Their study also takes into account infrastructure, by considering the region's accessibility by different means of transport. Although they find evidence that all three types of capital contribute to TFP formation, technological capital has the most essential impact, being significant at 1% level in all specifications. Vogel (2012) uses panel data from the manufacturing sector of 159 EU 15 regions and analyses both channels through which R&D and human capital can affect TFP: directly, through innovation and indirectly, through imitation. By allowing conditional convergence of TFP and regional spillovers, their results prove that human capital has a positive and direct effect on TFP, while R&D has a positive but indirect effect.

The health variable, considered to contribute to productivity as much as education, was first introduced in the growth models by Knowles and Owen (1995), who augmented the Mankiw *et al.* (1992) model and found a positive and significant relationship between health and economic growth. More recently, Cooray (2013) investigates the impact of health capital on economic growth disaggregated by income levels and finds that in higher and upper middle countries, health has a positive and robust influence on economic growth. Cole and Neumayer (2006) argue that a key mechanism through which health affects growth is through TFP. In the context of EU regions, there is no extensive study that considers the explicit impact of health on productivity. When assessing the productivity determinants in the Polish NUTS3 regions, Dańska-Borsiak and Laskowska (2012) construct a human capital index where, apart from considering education and technology aspects (e.g. number of students, percentage of graduates, Internet access), they also account for health aspects, proxied by number of visits to physicians. Although their results do show a positive impact of human capital on productivity, it is difficult to assess from their estimates the specific effect of the health variable on TFP.

PATTERNS OF THE EUROPEAN UNION REGIONS

This section describes the patterns in the evolution of TFP and its possible determinants that emerge in both EU15 and CEE regions. As it can be seen from Table 1, there are some important differences in the average values between the regions from the two blocks of countries. As expected, the differences in productivity are significant, with average TFP levels in EU15 more than 5 times higher than those in the CEE. When it comes to R&D intensity, EU15 regions also perform better, dedicating 3.5 times more resources to research than the CEE regions; however, their average intensity is still far from the EU target of 3 %. The difference is especially significant when it comes to R&D business, this sector is about one-fifth as large as a share of GDP in the CEE as compared to the EU15. It is important to note that in the EU15 regions most of the R&D is carried out in the private sector, while in the CEE regions the public sector has the leading role in R&D activity. Even so, public sector R&D in the CEE regions is less than one-half as large as in the EU15.

There are also major differences when it comes to the health variable. The EU15 regions have around 1.3 doctors per working age person, while in the

Table 1: Average values of possible TFP determinants

	EU15	CEE	Total
TFP levels	11.71	2.15	9.76
R&D total intensity (% in GDP)	1.54	0.44	1.32
R&D business intensity (% in GDP)	0.91	0.17	0.76
R&D public intensity (% in GDP)	0.63	0.29	0.57
Health (No. of doctors per working age population 15–64)	0.47	1.31	1.07
Infrastructure (km of roads)	18022	18879	18210

Note: R-square values are 0.23 for (TFP-R&D total); 0.14 for (TFP-R&D public); 0.22 for (TFP-R&D business); 0.03 for (A-no of doctors 15–64).
Source: Own computations based on EUROSTAT (2013) data

CEE regions it is about one-third as large. The differences in infrastructure, on the other hand, are very small, with CEE and the EU15 regions having about the same amount of roads.

The plots from Figure 1 show a fairly linear relationship between average productivity and the determinants we have considered. There seems to be a positive relationship between TFP and total R&D intensity. This trend is maintained also in the public and private sector, with the relationship stronger (higher R-square) in the private sector. The regions of the CEE distinguish themselves from the rest of the regions, in the lower left corner of the scatter plots, as having low productivity and low R&D intensity. The relationship between TFP and health, although positive, seems to be rather weak when no other factors are being considered.

The patterns presented here point towards a potential relationship between TFP and the determinants we are looking at. Also, the major

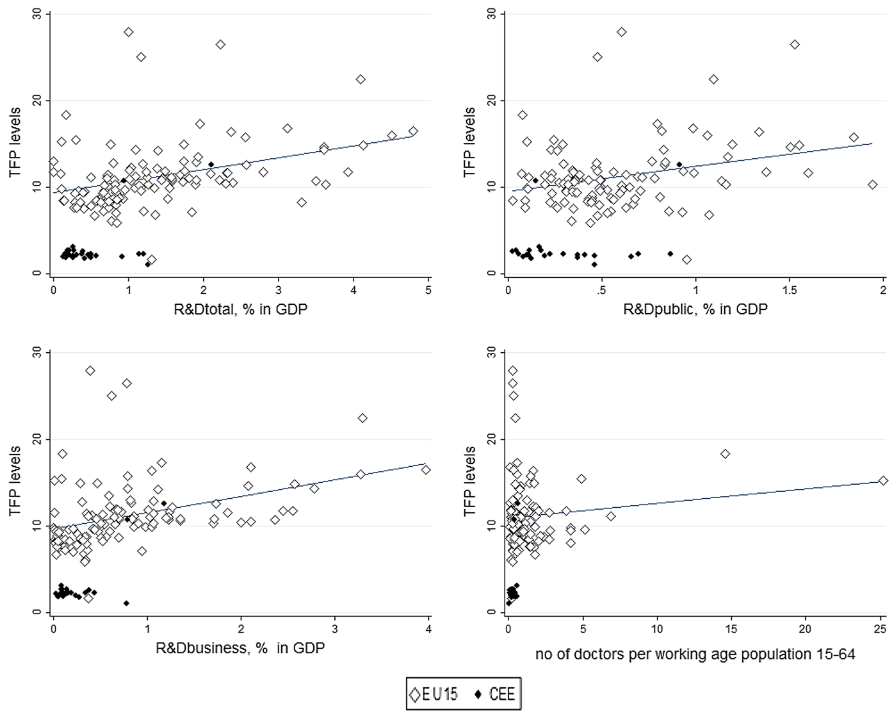

Figure 1: Scatter plots depicting the relationship between TFP and the following: total R&D, public R&D, business R&D and number of doctors per working age population
Source: Own processing based on EUROSTAT(2013) data

differences between EU15 and CEE regions in terms of productivities, R&D intensity and R&D structure confirm the need for considering two different production functions. Further, we will estimate this relationship in a panel data frame, considering various robustness specifications.

DATA, VARIABLES AND METHODOLOGY

The econometric model

To estimate the determinants of TFP in the EU regions, the following baseline equation was employed:

$$\ln A_{i,t} = \beta_0 \ln A_{i,t-1} + \beta_1 \ln \mathrm{HC}_{i,t} + \beta_2 \ln \mathrm{RD}_{i,t} + \beta_3 \ln \mathrm{INFR}_{i,t} + \eta_i + \varepsilon_{i,t}, \quad (1)$$

where $A_{i,t}$ is Total Factor Productivity, expressed in levels, computed from Cobb–Douglas production function with constant returns to scale, i.e. $Y = AK^{\alpha}L^{1-\alpha}$, as discussed below. Different capital share estimates are used for the EU15 ($\alpha = 0.3$) and CEE ($\alpha = 0.6$) regions. We prefer a parsimonious specification of the Cobb–Douglas production function as it is a simple one and represents a good starting point in studying TFP, dating back to Solow (1957). TFP expressed in *ln* can also be estimated from the logarithmic form of the Cobb–Douglas production function; however, this involves also estimating the input shares, which we have done in previous research for the CEE countries and it is beyond the scope of this paper. TFP can also be expressed in growth rates, easily derived from a growth accounting exercise; however, using growth rates instead of levels is considered to cause information loss in data and hence, lead to less preferred estimates; $A_{i,t-1}$ is the lagged dependent term, which shows the dynamic aspect of A. The fact that the creation of new knowledge is based on the existing stock of knowledge dates back to Romer (1990); β_0 may be interpreted as a factor of conditional convergence and expresses the catch-up effect towards the steady state. Conditional convergence, as explained under the neoclassical growth theory, allows each region to have a different level of productivity to converge towards; $\mathrm{HC}_{i,t}$ is the human capital variable, for which we used health as a proxy, measured by number of doctors per working age population (15–64 years)[1]; $\mathrm{RD}_{i,t}$ represents the total R&D investments, expressed as percentages in GDP. Further on, we split R&D into business R&D and public R&D, comprising government

[1]Other proxies for Human capital are also employed, such as life expectancy or health expressed as absolute number of doctors. However, no convincing results were obtained. We preferred to use the component of human capital that relates to health rather than education, at regional level.

and educational R&D; $\mathrm{INFR}_{i,t}$ is a proxy for infrastructure, for which we used the existent kilometres of road in the specific region; η_i is the region fixed effects that include time-invariant elements specific to a region and $\varepsilon_{i,t}$ represents the error term, assumed to be homoscedastic and with no serial correlation.

We have also introduced time dummies variables, to reduce the impact of time-specific effects across all regions and also to deal with the persistence of the series. As a first robustness check, we control for the regions which include the capital city, by introducing a country capital dummy variable. Country capitals are usually the largest cities in the country, and it is known that productivity tends to be higher in large cities and the areas around them. As Harris and Moffat (2012) point out, the diffusion and accumulation of knowledge is expected to be better in areas with many people and this also creates a spatial spillover effect that affects the surrounding region.

As mentioned, the level of TFP, the variable A_{it} is computed from a Cobb–Douglas specification, leading to the following equation:

$$A = \frac{Y}{L} \cdot \left(\frac{L}{K}\right)^{\alpha}, \tag{2}$$

where L is the labour stock measured by the working age population, aged 15–64, K is the capital stock, computed with a Permanent Inventory Method (PIM), using a depreciation rate of 5% for the CEE regions and 4% for the EU15 regions. PIM is used to compute the capital stock from past investment, depreciation and an estimate of an initial condition because direct measurement of the stock of capital is practically impossible. The depreciation rates chosen were based on the values used in the literature (Nehru and Dhareshwar 1993), as well as on the general assumption that the capital stock depreciates faster in developing countries, as these countries are normally engaged in a growth process based on capital accumulation and technology catching-up process.

$-\alpha$ is the capital input share, which was chosen based on the existing literature for EU15 and our own estimates for the CEE. The choice of capital share $\alpha = 0.6$ for the CEE regions is based on the authors' previous research results, see Pop Silaghi and Alexa (2015) and is backed up by similar studies. In that study, we use country level data for the 1993–2008 period and employing a labour-augmented Cobb–Douglas production function in order to avoid an over-inflated capital share. Our estimate of $\alpha = 0.6$ is consistent with other estimates for the CEE countries, see Iradian (2007) who also finds capital shares between 0.4 and 0.78 for the Central and South-Eastern Europe. A high value of alpha for the CEE regions makes sense because the stock of capital includes foreign direct investment. We did perform robustness checks by considering different values for α in the 0.4–0.6 interval and obtained estimations that are in line with the findings presented below.

To correct for possible endogeneity, we use a system GMM estimator. This estimator was developed by Arellano and Bover (1995) and Blundell and Bond (1998) building on the Arellano and Bond (1991) difference GMM. By exploiting additional moment conditions, system GMM allows the use of more instruments and hence, it is considered to be more efficient than the difference GMM estimator. Intuitively, based on the assumption it makes, the estimator permits the construction of a system of two equations: the differenced one, where lags of the dependent and independent variables are used as instruments, and the original one in 'levels' that use first differences as instruments. Besides its improved econometric efficiency, system GMM is considered to be more appropriate in growth empirics, as it could solve the problem of poor instruments caused by high persistence of independent variable (Bond *et al.*, 2001). By instrumenting the independent variables, the problem of endogeneity and double causality between the regressors and the independent variable is also addressed. As we will see below, system GMM also allows us to extend our model, by further considering spatial dependence.

Implementing spatial dependence

Although our dummy variable for regions that include the capital city captures some conglomeration and spatial effects, it does not properly account for the spatial dependence that may arise in our model. A majority of the growth models usually assume that the growth rates are randomly distributed across spatial units; however, this hypothesis might not be valid at a regional level. In recent years, following developments in spatial econometrics, it has become standard to account for spatial dependence in the context of regional growth. In our model, in the case of innovation, there could be spillovers from highly productive, highly innovative regions to surrounding regions which can lead to biased estimates for different determinants on TFP. Not accounting for spatial dependence works like an omitted variable bias (LeSage and Pace, 2009, p. 27) as part of the estimated effects may be in fact attributed to the geographical proximity between regions and not to the actual correlations between variables. Intuitively, spatial dependence can be introduced into the model in a nuisance form (spatial error term models) or in a substantive form (spatial autoregressive models), as stated by Anselin and Rey (1991). Although one would perform tests to choose between the two models, it is customary for the growth models to assume the second case, as it provides a meaningful interpretation (Kubis and Schneider, 2012) and it proves to be the most appropriate in a model of conditional convergence (Fingleton and Lopez-Bazo, 2006). Also, as Kubis and Schneider (2012) and Elhorst (2012) advocate, neglecting the spatial dependence in a substantive form is worse than neglecting the spatial autocorrelation in the error term, as it affects the consistency of the estimator. Based on this, by using the weight distance matrix W, we transform Equation (1) into a spatial autoregressive lag model:

$$\begin{aligned}\ln A_{i,t} = {} & \beta_0 \ln A_{i,t-1} + \rho W \ln A_{i,t} + \beta_1 \ln \mathrm{HC}_{i,t} + \beta_2 \ln \mathrm{RD}_{i,t} \\ & + \beta_3 \ln \mathrm{INFR}_{i,t} + \eta_i + \varepsilon_{i,t},\end{aligned} \tag{3}$$

where $W \ln A_{i,t}$ represents the spatially lagged dependent variable. The matrix W, which captures the effect of the interactions between neighbouring regions, is computed in our case as the inverse distance weighted matrix, illustrating the idea that the smaller the distance between regions, the higher the spatial dependence between them. To avoid unreasonable neighbourhood relationships over large distances, we are considering that there is no spatial interaction between regions that are more than 1000 km apart. The resulting matrix is row-standardised, as is usual in the literature.

There are now a variety of estimators that deal with spatially lagged variables in a data panel context; we use the approach of Monteiro and Kukenova (2009) which is also used in other empirical growth models (see Kubis and Schneider, (2012)). By means of Monte Carlo simulations, Monteiro and Kukenova (2009) show that directly estimating the System GMM with a spatially lagged dependent variable works reasonably well, outperforming the alternative estimation strategies in terms of bias and efficiency. We estimate Equation (3) in the same way as Equation (1), treating $W \ln A$ as an endogenous term and instrumenting it accordingly.

Data and model validity

For our estimations, we employed EUROSTAT data over the 1999–2010 period. In defining our geographical units of analysis, we follow "Nomenclature of Statistical Territorial Units" NUTS classification provided by EUROSTAT. We refer to the NUTS 2 regional level, since these regions have their own administration. Due to data availability, we use a limited number of the 123 NUTS regions, 96 belonging to EU15 and 27 to CEE countries.[2] The regions belong to 13 countries: Austria, Croatia, Finland, France, Germany, Italy, Netherlands, Poland, Romania, Slovenia, Spain, Sweden and United Kingdom. The choice of the regions included in our study (and therefore, of the countries) is subject to data availability in the EUROSTAT regional database. Different numbers of regions may appear in the estimation tables, as the split between public and business R&D is not available for all regions.

[2]The complete list of the NUTS2 regions used in estimations can be obtained from the authors.

To avoid short-term business fluctuations affecting the results, 5-year rolling averages were used. Our panels are balanced, due to the rolling averages used and each specification is tested for both EU15 and CEE regions. As robustness checks, we employ a different time frame—corresponding to the period before the 2004 EU enlargement—and we consider the impact of spatial dependence in our model, as described earlier.

In the case of system GMM, particular attention must be given to the validity of the instruments used. Because of our sample size, we could not employ all available lags as instruments, as one rule of thumb is to keep the number of instruments smaller than the number of groups. To achieve this, we have also used the 'collapsed' version of our instruments, as recommended by Roodman (2009). The combination lags used as instruments are described in the results (Tables 3, 4, 5), although various lag combinations showing similar results were tested. To test the validity of our instruments, we employed two tests: the Hansen Test and the Difference-in-Hansen test. In our case, the p values reported for Hansen Test are usually higher than 0.05, proving that both sets of instruments—for the level and differenced equations—are fairly valid. The Difference-in-Hansen test inquires the validity of the "GMM-style" instruments for the levels equations, which should be valid for the system GMM to be consistent. Again, the p values for this test indicate that our system GMM is robust in most of the cases. We also checked for stationarity in our data, as it is known that the presence of unit roots in series can lead to spurious results. To test for panel unit root processes, we employed a Fisher-type test which performed an ADF unit root test on each panel and then used the inverse normal transformation on the p values to obtain the overall test for the panel series. This test is suitable for our T and N dimension and also allows for different autoregressive parameters across the panels. The inverse normal transformation we used was considered by Choi (2001) as the most suitable, both in cases of finite and infinite N. The results of the panel data unit root test, as described in Table 2, generally reject the null hypothesis of random walk processes both in the case of EU15 and CEE. Although in the case of infrastructure variable in EU15 the null hypothesis seems to be accepted, the p value is still small ($p = 0.118$) so we do not consider that it represents a problem for our model.

RESULTS

The estimates of Equation (1) for EU15 and CEE regions are presented in Table 3. Column 1 shows the effect of health variable, total R&D and infrastructure on TFP in the EU15 regions. Column 3 differentiates between

Table 2: Panel unit root test results

	EU15		CEE	
	Z-statistic	*p* Value	Z-statistic	*p* Value
lnA	−11.630	0.000	−1.683	0.046
lnhealthdoctors15_64	−14.201	0.000	−4.031	0.000
lnrdtotal	−8.045	0.000	−4.231	0.000
lnrdbusiness	−8.020	0.000	−5.833	0.000
lnrdpublic	−8.019	0.000	−5.971	0.000
lnroads	−1.186	0.118	−6.574	0.000

A Fisher-type panel unit root test was employed, based on the ADF tests for each panel.
Panel-specific AR term was considered, with fixed effects, drift term and 1st lag for the ADF regressions. Inverse normal Z-statistic was reported, suitable for both finite and infinite N. The test assumes null hypothesis *Ho: All panels contain unit roots*, with the alternative *Ha: At least one panel is stationary*.
Source: Own estimations based on EUROSTAT (2013) data

business and public R&D in the process of TFP formation. In columns (2) and (4), the impact of the region containing the country capital is added to the specifications in columns (1) and (3), respectively. The same four models are then re-estimated for the CEE regions in columns (5)–(8). The results indicate that the number of doctors per working age population seems to have a significant impact on TFP in both EU15 and CEE regions; however, the effect is stronger and more stable in the EU15 regions. Total R&D is significant both in EU15 and CEE regions and when we separate between business and public, only public R&D remains significant in the EU15 regions. Infrastructure also appears to have an impact, especially in the CEE regions.

The robustness check considering the period after the 2004 EU enlargement indicates total R&D and public R&D as drivers of TFP in the EU15 regions, whereas in the CEE regions infrastructure seems to be a fairly robust driver of productivity (Table 4). The health variable stays significant only in one equation for EU15 regions. It is known that having access to a larger market and benefiting from unrestricted trading of goods, people and ideas may have a stimulating effect on productivity and innovation. However, this effect is not verified for our CEE regions—it might take more time for the benefits of being part of an economic union to pay off.

Including the country capital city affects the impact of R&D on productivity in the EU15 regions, both in Table 3 and Table 4. The effect of R&D decreases when we account for the region that includes the capital of the country. This suggests that most of the innovative R&D activity is absorbed in these country capital regions. This impact is more robust with public R&D than it is with total R&D. The result is expected since regions where the capital

Table 3: Determinants of total factor productivity in the European regions

	(1) EU15	(2) EU15	(3) EU15	(4) EU15	(5) CEE	(6) CEE	(7) CEE	(8) CEE
$\ln A_{i,t-1}$	0.837***	0.811***	0.785***	0.760***	0.939***	0.900***	0.983***	0.982***
	(0.074)	(0.091)	(0.097)	(0.115)	(0.034)	(0.048)	(0.090)	(0.063)
$\ln HC_{i,t}$	0.068**	0.063*	0.073**	0.056	0.076**	0.064*	0.038	0.031
	(0.030)	(0.037)	(0.029)	(0.065)	(0.029)	(0.035)	(0.052)	(0.058)
$\ln RDtotal_{i,t}$	0.057***	0.049**			0.051**	0.048**		
	(0.016)	(0.021)			(0.021)	(0.019)		
$\ln RDbusiness_{i,t}$			0.009	0.000			0.022	0.031
			(0.031)	(0.025)			(0.056)	(0.054)
$\ln RDpublic_{i,t}$			0.126**	0.106*			0.051	0.059
			(0.049)	(0.063)			(0.048)	(0.039)
$\ln INFR_{i,t}$	0.040	0.037	0.028	0.032	0.065***	0.082***	0.034	0.033
	(0.027)	(0.030)	(0.021)	(0.029)	(0.017)	(0.027)	(0.053)	(0.044)
$Countrycapital_{i,t}$		0.109		0.295		0.153		−0.080
		(0.269)		(0.372)		(0.121)		(0.077)
No of regions	96.000	96.000	89.000	89.000	27.000	27.000	23.000	23.000
No of obs	659.000	659.000	579.000	579.000	171.000	171.000	128.000	128.000
Hansen Test[a]	0.114	0.134	0.464	0.687	0.203	0.429	0.474	0.461
Diff in Hansen[a]	0.502	0.436	0.274	0.628	0.242	0.289	0.622	0.605
AR(2)[a]	0.086	0.059	0.143	0.312	0.288	0.099	0.245	0.239
No of instruments	25.000	25.000	27.000	27.000	25.000	25.000	27.000	27.000

Note: Standard errors in brackets. *, ** and *** denote significance levels of 10, 5 and 1 %, respectively.
Method used is system GMM, with robust standard error, consistent with panel-specific autocorrelation and heteroskedasticity in two-step estimation.
All regressions include time fixed effects.
Instruments for the first-difference equation: the 4th up to the 7th lag of $\ln A_{i,t-1}$, the 3rd and 4th lag of $\ln HC_{i,t}$, $\ln RDtotal_{i,t}$, $\ln RDbusiness_{i,t}$, $\ln INFR_{i,t}$ (collapsed), the 4th lag of $\ln RDpublic_{i,t}$ (collapsed).
Instruments for the levels equation: the first difference of the lagged dependent and independent variables. Different lags combinations were also tested for the first-difference equation.
[a] *p* values are reported.
The capital share used for computing TFP was 0.3 for EU15 regions and 0.6 for the CEE regions.
Source: Own estimations based on EUROSTAT (2013) data

Table 4: Robustness check: determinants of total factor productivity in the European regions after the 2004 EU enlargement

	(1) EU15	(2) EU15	(3) EU15	(4) EU15	(5) CEE	(6) CEE	(7) CEE	(8) CEE
$\ln A_{i,t-1}$	0.854***	0.846***	0.741***	0.728***	0.992***	0.957***	0.983***	0.993***
	(0.079)	(0.083)	(0.045)	(0.051)	(0.053)	(0.070)	(0.084)	(0.080)
$\ln HC_{i,t}$	0.037	0.049	0.066**	0.073	0.036	0.049	0.034	0.002
	(0.028)	(0.047)	(0.032)	(0.067)	(0.049)	(0.054)	(0.102)	(0.092)
$\ln RDtotal_{i,t}$	0.059***	0.053***			0.028	0.029		
	(0.017)	(0.019)			(0.042)	(0.039)		
$\ln RDbusiness_{i,t}$			0.010	0.001			0.021	0.039
			(0.018)	(0.027)			(0.080)	(0.059)
$\ln RDpublic_{i,t}$			0.114**	0.110*			0.034	0.054
			(0.046)	(0.060)			(0.033)	(0.037)
$\ln INFR_{i,t}$	0.010	0.018	0.042**	0.044**	0.070**	0.073**	0.041	0.020
	(0.032)	(0.028)	(0.020)	(0.020)	(0.033)	(0.033)	(0.041)	(0.047)
$Countrycapital_{i,t}$		0.091		0.242		0.079		−0.070
		(0.300)		(0.449)		(0.132)		(0.082)
No of groups	96	96	89	89	27	27	23	23
No of obs	568	568	495	495	148	148	113	113
Hansen Test[a]	0.238	0.203	0.579	0.560	0.108	0.068	0.168	0.095
Diff in Hansen[a]	0.134	0.163	0.372	0.412	0.118	0.020	0.122	0.051
AR(2)[a]	0.281	0.240	0.393	0.520	0.128	0.279	0.362	0.382
No of instruments	20	20	23	23	20	20	23	23

Note: Standard errors in brackets. *, ** and *** denote significance levels of 10, 5 and 1%, respectively.
Method used is system GMM, with robust standard error, consistent with panel-specific autocorrelation and heteroskedasticity in two-step estimation.
All regressions include time fixed effects.
Instruments for the first-difference equation: the 4th up to the 7th lag of $\ln A_{i,t-1}$, the 3rd and 4th lag of $\ln HC_{i,t}$, $\ln RDtotal_{i,t}$, $\ln RDbusiness_{i,t}$, $\ln INFR_{i,t}$ (collapsed), the 3rd and 4th lag of $\ln RDpublic_{i,t}$ (collapsed).
Instruments for the levels equation: the first difference of the lagged dependent and independent variables. Different lags combinations were also tested for the first-difference equation.
[a] *p* values are reported.
The capital share used for computing TFP was 0.3 for EU15 regions and 0.6 for the CEE regions.
Source: Own estimations based on EUROSTAT (2013) data

city is situated are the most competitive regions in their respective countries (see Annoni and Dijkstra (2013)); there is a conglomeration of human capital, innovative companies and universities that boost productivity. Research carried out in public institutions (universities, public institutions) seems to be of particular interest here, as their effect on R&D is shown to be significant and robust. However, for the sake of reducing disparities, innovation measures should target other regions as well.

The results in Table 5 present an autoregressive spatial lag of the dependent variable, taking into account the fact that the TFP in one region may be influenced by that in a neighbouring region. We are aware that in our model the spatial autocorrelation of the dependent variable cannot be fully tested, as we are not employing all existing EU regions, so the insignificance of ρ (the coefficient on $W\ln A_{i,t}$) should be interpreted carefully. The results do point out that spatial proximity has an effect on productivity and also on the way in which some factors contribute to the creation of TFP. These spatial effects are less visible on the health variable, for which the coefficient stays significant at the same level in the EU15 and CEE region samples. It can be seen, however, that for the R&D variable, in most of the cases its significance drops, as it is the case in columns (1), (2) and (6). Especially when the effect of the capital city is considered, total R&D becomes insignificant, both in EU15 and CEE. Public R&D seems to be more robust to the spatial autocorrelation, while for the EU15 its effect remains the same.

Out of all the considered determinants of TFP, the most robust seem to be public R&D, whose impact is quite strong on the productivity among the EU15 regions. Our results also point out that most of these R&D activities are carried out in regions which include the country capital, reinforcing the idea that innovation in EU regions is not a homogenous process. R&D as a whole has a significant impact in the regions of the EU15 and CEE; however, its effect is influenced by both spatial dependence and conglomeration effect of the country capital. From our results, nothing can be said about business R&D. It is true that the innovation in the private sector is not always accounted by the business R&D variable and this makes it difficult to properly quantify the effect of firms' innovation on TFP. Therefore, our results seem to support investments in public R&D in EU15 regions.[3] For the CEE regions, although there is evidence of the total R&D impact on TFP, the sector where it manifests itself is less clear. One argument in favour of a significant impact of public R&D is also enforced by the European Commission (2014), stating that the

[3]In an earlier paper (Pop-Silaghi *et al.*, 2014), we assessed the impact of private and public R&D on the economic growth rates at a national level, just for CEE countries. Our results showed that private R&D was significant and its effect was robust in many specifications.

Table 5: Robustness check: accounting for spatial dependence when assessing determinants of TFP in European regions

	(1) lnA b/se	(2) lnA b/se	(3) lnA b/se	(4) lnA b/se	(5) lnA b/se	(6) lnA b/se	(7) lnA b/se	(8) lnA b/se
$\ln A_{i,t-1}$	0.798***	0.764***	0.821***	0.795***	0.928***	0.900***	0.955	0.961*
	(0.141)	(0.208)	(0.073)	(0.087)	(0.035)	(0.051)	(5.232)	(0.558)
$W\ln A_{i,t}$	−0.066	−0.055	0.032	0.007	0.037	0.133	0.220	0.229
	(0.131)	(0.075)	(0.074)	(0.054)	(0.146)	(0.157)	(18.630)	(1.832)
$\ln HC_{i,t}$	0.062**	0.064*	0.080***	0.064*	0.069**	0.055*	−0.009	0.016
	(0.029)	(0.034)	(0.022)	(0.032)	(0.032)	(0.029)	(4.411)	(0.289)
$\ln RDtotal_{i,t}$	0.058**	0.056			0.060***	0.031		
	(0.023)	(0.038)			(0.018)	(0.019)		
$\ln RDbusiness_{i,t}$			0.011	0.014			0.023	0.013
			(0.018)	(0.017)			(3.866)	(0.273)
$\ln RDpublic_{i,t}$			0.098**	0.096*			0.050	0.042
			(0.041)	(0.048)			(1.740)	(0.304)
$\ln INFR_{i,t}$	0.040*	0.048	0.039**	0.033	0.058***	0.078*	0.015	0.026
	(0.023)	(0.040)	(0.016)	(0.023)	(0.017)	(0.040)	(2.324)	(0.301)
$Countrycapital_{i,t}$		0.074		−0.067		0.188		0.057
		(0.292)		(0.212)		(0.168)		(1.316)
No of groups	96	96	89	89	27	27	23	23
No of obs	659	659	579	579	171	171	128	128
Hansen Test	0.190	0.216	0.218	0.291	0.234	0.286	0.682	0.696
Difference-in-Hansen	0.535	0.353	0.225	0.308	0.290	0.120	0.413	0.822
AR(2)	0.039	0.041	0.029	0.050	0.239	0.127	0.973	0.824

Table 5: (*Continued*)

	(1) lnA b/se	(2) lnA b/se	(3) lnA b/se	(4) lnA b/se	(5) lnA b/se	(6) lnA b/se	(7) lnA b/se	(8) lnA b/se
No of instruments	27	27	29	29	27	27	29	29

Note: Standard errors in brackets. *, ** and *** denote significance levels of 10, 5 and 1%, respectively.
Method used is system GMM, with robust standard error, consistent with panel-specific autocorrelation and heteroskedasticity in two-step estimation.
All regressions include time dummies fixed effects.
Instruments for the first-difference equation: the 4th up to the 7th lag of $\ln A_{i,t-1}$, the 3rd and 4th lag of $\ln HC_{i,t}$, $\ln RDtotal_{i,t}$, $\ln RDbusiness_{i,t}$, $\ln INFR_{i,t}$ (collapsed), the 4th lag of $\ln RDpublic_{i,t}$ (collapsed), the 4th lag of $W\ln A_{i,t}$ (collapsed).
Instruments for the levels equation: the first difference of the lagged dependent and independent variables. Different lags combinations were also tested for the first-difference equation.
[a] *p* values are reported.
The capital share used for computing TFP was 0.3 for EU15 regions and 0.6 for the CEE regions.
Source: Own estimations based on EUROSTAT (2013) data.

effects of public R&D are seen across all the economy, even in the private sector, as public R&D generates the knowledge base and talent that private R&D needs.

Until now, health has been ignored as a determinant for total productivities in the European regions. Although generally significant and robust to spatial dependence, its effect fades after the second EU enlargement. Infrastructure also has an effect that is especially visible in the CEE regions. Infrastructure allows regions to be better connected and to expand their productivity by engaging in commercial and institutional exchanges. Especially in the case of CEE, this seems to be a crucial factor, as historical and economic constraints have impeded them to fully benefit from commercial transactions. From this point of view, our paper encourages further investments in infrastructure.

Our results also point out the conditional convergence process that it is taking place, in both EU15 and CEE, the regions are converging towards their own steady-state productivity. Although this does not represent an indicator that regional disparities are being reduced, conditional convergence both within EU15 and CEE regions is a good sign, as it may be 'a necessary (but not sufficient) condition of sigma convergence' to take place (Young, *et al.*, 2008).[4]

CONCLUSIONS

This paper assessed the impact of determinants of TFP across 96 EU15 regions and 27 CEE regions during 1999–2010, by employing variables such as R&D, human capital and infrastructure. We not only looked at the effect of total R&D intensity, but also disaggregated it by sectors of activity, namely public R&D and private R&D. As a measure for human capital, we used a health indicator, the number of doctors per working age population in a given region. Based on the recent literature, we also introduced an infrastructure variable, proxied by the kilometres of roads in a given region. We also controlled for spatial dependencies by introducing a spatial lag in our main estimations. In order to eliminate any business cycle effects, we used 5-year rolling averages. We employed system GMM estimator, controlling for possible endogeneity within our variables.

[4]For the CEE regions, the results obtained in Table 3 for column (5) and (8) remain fairly robust for different capital share specifications (alpha between 0.45 and 0.60), confirming one of the main findings of this paper for the CEE: over the studied period, in the CEE regions, total R&D, health and infrastructure have positive impact on TFP. These results are available upon request.

Our findings support the importance of R&D as a positive and robust determinant of productivity, especially in the case of EU15. A conditional catch-up process in terms of TFP seems to take place, and this can continue if R&D is supported in the future, and also if additional factors, ignored until now, such as health, are taken into consideration. Our study brings additional evidence that human capital proxied this time by a health dimension which seemed to us a suitable proxy at regional level, has a positive influence on TFP. Infrastructure, especially in CEE regions, counts for increasing total factor productivity. While robustness checks are performed, taking into account the year of the first enlargement of the European Union, health and public R&D remain significant solely for the EU 15 regions. When the capitals cities of each county are considered, the effect of R&D decreases, however, with the public R&D effect being robust to the impact of spatial autocorrelation.

Decreasing regional disparities is a challenge for policy makers, so as to be able to emphasise policies that are suitable for all the EU member countries. In order to do so, finding and knowing the factors that can stimulate economic growth, in a direct way or indirectly by positively influencing the total factor productivity, constitute a priority. Considering three sources of productivity that are recognised as potential drivers of growth, both at national and regional level, for all regions of EU, based on data availability, represented both a challenge and a desire to reveal some facts about regions inside EU and their expected (or not) convergence. Finding a way through which health is sustained at regional levels, no matter if the rural areas are prevalent, should be a major concern of the policy makers. As we could notice, health was significant for both EU 15 and CEE, proving that if medical services are offered and thus, normally, the probability of people being healthier if treated is higher. This positive aspect may be seen in their performance at work, which means an increased level of productivity. Finding channels of cooperation between public and private sectors that invest in R&D could sustain long-term economic growth rates at the regional levels and also high levels of total factor productivities. Last, but not least, infrastructure, especially in CEE regions, should be improved so as to permit these regions to develop more, based on internal trading between them inside each country and also based on better labour mobility that would contribute to reducing disparities, firstly inside the country and secondly, between them and other similar regions from neighbouring countries.

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