

The contributions of human capital, R&D spending and convergence to total factor productivity growth

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ABSTRACT: The study investigates the drivers of total factor productivity (TFP) growth, covering 99 European regions from 31 countries over the period 2000–13. It shows that human capital endowment had a positive effect upon TFP growth, particularly in advanced regions, but the effect from regions' own research and development (R&D) expenditures was largely absent. The effects of human capital and R&D on TFP growth varied with the productivity gap. Further, there was a threshold effect in convergence, where stronger TFP growth was associated with both a larger productivity gap and a higher initial level of productivity. Spatial spillover effects had a positive impact upon TFP growth.

KEYWORDS: total factor productivity (TFP), convergence, human capital, research and development (R&D), productivity gap and frontier

JEL CLASSIFICATION: I25, O30, O47, R11

INTRODUCTION

More than one-quarter of a century after the collapse of the Eastern Bloc, and more than a decade after they joined the European Union (EU), the countries of Central and Eastern Europe (CEE) still lag behind Western Europe in productivity, and there is a substantial and persistent income gap between the regions of 'Old' and 'New' Europe. After an initial period of rapid convergence, economic growth has slowed in the CEE regions, making it harder for them to catch up with the more advanced parts of Europe. Like the middle-income regions of Latin America and the Middle East that have been held in the middle-income trap for decades (Gill et al., 2007), the CEE seems to be caught in the trap. As differences in productivity rates are the source of almost all per capita income disparities across economies (Syverson, 2011), it is crucial for the CEE regions to find means of speeding up their productivity growth, as this is the primary source of sustainable, long-term economic development. However, productivity growth is also vital for the advanced economies in Europe if they are to compete with the United States and other rising economic powers in the global marketplace. Further, several southern European regions that have been affected severely by the sovereign debt crisis need to find a way to restart their economies and boost productivity. Finally, it is important for countries to reduce the regional disparities within their borders and ensure a sustained increase in the well-being of all their citizens.

The current study investigates how total factor productivity (TFP) growth is affected by the quality of human capital resources ('endowment'), the commitment to sustainable research and development (R&D) financing ('commitment'), and the regional location and the disparities surrounding the prevailing frontier of knowledge and productivity ('convergence'). In simple terms, productivity denotes the efficiency with which production factors, or inputs, are converted into products, or output. Researchers commonly use TFP as their productivity measure of choice as it is invariant to the intensity of observable factor inputs, making it preferable to single-factor productivity measures such as labour productivity (see Syverson, 2011, for a detailed overview of the ever-growing research into productivity).

The study sample involves 99 NUTS-1 level European regions from 31 countries, in a timeframe from 2000 to 2013. The analysis uses annual data retrieved from EUROSTAT regional statistics. The key factors under investigation are the convergence effects expressed in the TFP gap and spatial spillovers along with each region's own R&D expenditures and their human capital endowment. A Schumpeterian growth model is used in which the region's productivity gap relative to the frontier is taken as a direct measure of convergence and as a source of indirect effects via interaction terms with the human capital endowment and with R&D investments. Spatial productivity spillovers across regions are investigated using a multidimensional distance matrix accounting for the geographical latitude, longitude and location of the regions within or outside the same national territory.

The study contributes to the discussion on economic growth and productivity by disentangling the effects of the human capital endowment and the R&D contribution and both the TFP convergence and impact of technology spillovers by employing the efficient, dynamic panel generalized method of moments (GMM) estimator, which accounts for the self-reinforcing feedback effects between TFP growth, R&D investment and human capital (see Nelson & Phelps, 1966, for theoretical arguments; see Capello & Lenzi, 2015, for empirical evidence). Further, the study sample enables good contrast including regions from both advanced Europe and the CEE. The CEE regions are a valuable source of empirical evidence for investigating the drivers of productivity at varying levels of it, given their background where the formal qualifications of the human capital are at a high level, while there is a comparatively weak record of cutting-edge research and technological achievements.

The results of the estimation largely confirm our expectations. The TFP gap is a significant determinant of TFP growth, with regions that lag behind the productivity frontier growing faster than regions closer to the frontier. The main effects of human capital and R&D expenditures are positive. The regional, or spatial, productivity spillover effects are significant, stressing the importance of the spatial dimension in productivity growth. The results also suggest strong path dependencies, as a very weak starting position in the level of TFP had an adverse effect on further productivity convergence. We observe in the interactions of the TFP gap with human capital endowment and R&D expenditures that there are marked differences between the regions of advanced and emerging Europe. In advanced Europe, the marginal return on human capital and R&D is a decreasing one as less productive regions gain relatively more from human capital and R&D. In contrast, only the most productive regions gain from increases in human capital endowment and R&D investment in CEE. This could imply a process of regional convergence in advanced Europe and a trend towards regional divergence in emerging Europe. Policies that promote stronger harmonization and better connectedness between peripheral regions and high-productivity core Europe through improved transportation and, more recently, through digital channels and a single digital market might combat fragmentation and lead to a more open, competitive and transparent business environment throughout Europe.

The paper is organized as follows. The next section provides a brief survey of the literature on economic growth along with the main points in the contemporary literature on productivity drivers, convergence and regional spillovers. The third and fourth sections present the methodology, specify the empirical model and describe the data. The fifth section discusses the main results. The final section draws conclusions and policy implications. Summary statistics, robustness checks and the list of NUTS-1-level regions are presented in Appendices A–D.

A BIRD'S-EYE VIEW OF ECONOMIC GROWTH, R&D AND HUMAN CAPITAL

Endogenous growth, productivity and absorptive capacity

The connection between economic growth, R&D and human capital has theoretical foundations in the literature on endogenous growth that started to emerge in the second half of the 1980s (Aghion &

Howitt, 1992; Grossman & Helpman, 1991; Lucas, 1988; Romer, 1986, 1990) and was rooted in neoclassical growth theory, as most famously embodied in the model presented by Solow (1956) in which long-term growth is exogenous. Endogenous growth theory is intended to explain the drivers of technological progress, which is the source of long-term economic growth. In the model by Romer (1990), growth is driven by technological change creating increased productivity, as the variety of intermediate goods increases because of the intentional investment decisions made by profit-maximizing agents. Aghion and Howitt (1992) propose a Schumpeterian model where technological progress is modelled as occurring in the form of innovations. Research firms use these innovations to improve the quality of existing intermediate goods, and this then renders the existing line of goods obsolete. Funke and Strulik (2000), however, propose a single model that accommodates both the standard neoclassical growth model and modern endogenous growth theory and explains growth at different stages of economic development.

Romer (1990) and Aghion and Howitt (1992) credit R&D and human capital with a substantive role in driving economic growth. Research activities and human capital also take centre stage in the literature on absorptive capacity, a concept first put forward in two seminal papers by Cohen and Levinthal (1989, 1990). In this concept, R&D has two faces. First, research creates new knowledge through innovation; and second, it develops absorptive capacity, or the ability to identify, assimilate and make use of outside knowledge. This means that how much technological progress a country, region or industry makes depends on how much it can innovate and how much capacity it has for exploiting external knowledge. R&D and human capital are important for both of these, and together they can raise the capability to create innovation and imitate the creations of others.

Griffith, Redding, and Van Reenen (2003) offer a single integrated framework that combines Schumpeterian endogenous growth theory with the empirical literature on R&D, productivity growth and productivity convergence. They extend Aghion and Howitt's (1992, 1998) Schumpeterian model to show that R&D-induced innovation, R&D-based absorptive capacity and technology transfer are all determinants of TFP growth. Griffith et al. note that while all countries behind the technological frontier have the potential to achieve productivity growth through technology transfer, or convergence, the realization of this potential is also dependent on R&D-based absorptive capacity, meaning there may be long-run disparities between countries. This comprehensive approach forms the basis for the empirical framework of the current paper, as described further in the third section.

R&D and human capital as drivers of productivity growth

Numerous empirical studies have been investigating the roles of R&D and human capital in stimulating economic growth. Griffith, Redding, and Van Reenen (2004) employ data on 12 Organisation for Economic Co-operation and Development (OECD) countries over the period 1974–1990 and follow the approach developed by Griffith et al. (2003), finding strong evidence that R&D stimulates growth directly through innovation, and also indirectly as national industries that lag behind the productivity frontier catch up particularly quickly if they invest heavily in R&D. They also establish a significant link between human capital and productivity growth. Similarly, Islam (2009) exploits a panel of 55 developed and developing countries over the period 1970–2004 and discovers that both research intensity and distance to the productivity frontier have a significant positive effect on productivity growth. In addition, human capital and R&D-driven absorptive capacity accelerate productivity growth. However, the author notes that the effect of absorptive capacity is very sensitive to model specification and the measurement of innovative activity.

Havik, McMorrow, and Turrini (2008) explore the determinants of the TFP growth gap between the EU and the United States and show that TFP growth appears to be driven by a catching-up phenomenon associated with the gradual adoption of new technologies. They also reveal that progress at the technological frontier accelerates TFP growth. Colino, Benito-Osorio, and Rueda-Armengot

(2014), using data on 26 OECD countries from the period 1965–2010, find that the domestic research effort has a positive and significant consequence for TFP in countries that are close to the technological frontier. However, less advanced countries can reap greater benefits from foreign direct investment (FDI) and from importing technically advanced goods. Gehring, Martinez-Zarzoso, and Nowak-Lehmann Danzinger (2014) examine a panel of 17 EU countries over the period 1995–2007 and conclude that the main drivers of TFP in the manufacturing sector are rationalization, human capital endowment, and investment in information and communication technologies. Additionally, they control for FDI, R&D and openness, but do not find evidence for a significant link between these factors and TFP. The authors suggest this might be because the role of FDI, R&, and openness varies widely from sector to sector and from country to country.

Although several empirical papers (e.g., Griffith et al., 2004; Gehring et al., 2014) have found that human capital drives economic growth, some studies have not identified such an effect (e.g., Cameron, Proudman, & Redding, 2005). Fuente and Domenech (2006) claim that data deficiencies are at least partially responsible for poor measurement and the weak empirical performance of human capital indicators in growth equations. Islam, Ang, and Madsen (2014) stress the importance of both the quantity and quality of human capital. Folloni and Vittadini (2010) proxy the value of human capital using, among other measures, the data on student performance in ability tests. However, Chen and Luoh (2010), using test scores in mathematics and science to measure the quality of the labour force, show that after controlling for a number of other variables explaining cross-country economic growth, the variables such as R&D researchers per capita or scientific and technical journal articles per capita can better account for the cross-country income differences.

Role of regional spillovers in productivity convergence

There appears to be an important link between geography and productivity. Krugman (1991) started the discussion on regional economics and economic geography by proposing a theory of geographical concentration of manufacturing. Audretsch and Feldman (1996) show that innovative activity is more likely to cluster in industries where knowledge spillovers are more common. While geographical concentration of production also tends to be larger in these industries, the results suggest that clustering is driven more by knowledge spillovers than by the geographical concentration of production. Using company accounts data from five developed countries, O'Mahony and Vecchi (2009) show that productivity is higher in R&D and skill-intensive industries, interpreting this as evidence of knowledge spillovers.

The improved availability of regional data and the rapid development of methods and tools for spatial analysis have opened an avenue for a number of empirical papers that explore the regional aspects of economic growth. Looking at the spatial correlation between variables, Badinger, Müller, and Tondl (2004) investigate income convergence in a panel of European NUTS-2 regions for the period 1985–99 and obtain a speed of convergence of 7%. Varga and Schalk (2004) examine data on 19 Hungarian counties from the period 1998–2000 and suggest that localized knowledge spillovers play an important role in TFP growth. Funke and Niebuhr (2005) focus on West German regions and also find evidence in support of knowledge spillovers, noting that significant spillovers are mainly to be found in geographically proximate regions. Rodríguez-Pose and Crescenzi (2008) estimate the effect of R&D, spillovers and innovation systems on regional per capita gross domestic product (GDP) in the EU-25 countries. Their results show productive knowledge spillovers are subject to geographical boundedness within a radius of about 200 km. They also find that R&D investments do not yield the expected returns in peripheral regions.

Dettori, Marrocu, and Paci (2012) show that a large part of the TFP variation across regions of the EU-15 plus Switzerland and Norway in the period 1985–2006 is explained by disparities in human, social and technological capital endowments. O'Leary and Webber (2015) study the role of structural change in the productivity growth of NUTS-2 regions in 13 EU countries in the period 1980–2007. Their

results stress how important intersectoral structural change is for productivity growth. Capello and Lenzi (2015) focus on knowledge, innovation and TFP gains across the EU-15 and EU-12 regions. They show that TFP gains in less R&D-intensive regions are linked more strongly to human capital than to investment in R&D. Vogel (2015) investigates the determinants of TFP growth in the manufacturing sectors of 159 NUTS-2 regions in the period 1992–2005. The author suggests that regional R&D aids the absorption of technology spillovers from geographically close regions, while human capital raises productivity growth in regions closer to the productivity frontier. Marrocu, Paci, and Usai (2011) examine the effects of agglomeration externalities on TFP growth in the regions of the EU-27 in the period 1996–2007, uncovering a more disparate pattern of TFP growth paths in the advanced regions of the older EU member states than in the emerging regions of the newer EU members. Using a panel of 255 NUTS-2 regions from the period 1995–2005, Cuaresma, Doppelhofer, and Feldkircher (2014) study the determinants of income per capita growth in Europe. The results suggest that income convergence between countries is primarily driven by the catching-up process in the CEE, while convergence within countries is mostly attributable to developments in older EU member countries. Further, the authors find that regions that contain capital cities, especially in the CEE, or that have better educated workers grow faster, and that the results are similar when spatial spillovers are allowed for. Beugelsdijk, Klasing, and Milionis (2017) investigate the TFP of 257 NUTS-2 regions in 21 EU countries and show that large TFP differences exist even within countries and that these disparities are significantly related to both economic geography and earlier development paths.

Both Canova (2004) and Corrado, Martin, and Weeks (2005) discuss convergence clusters. Canova (2004) proposes that convergence clubs signify the tendency of the income per capita of countries or regions to ‘cluster around a small number of poles of attraction’. By applying a new procedure for identifying convergence clubs to both European regional data and data from OECD countries, the author finds evidence of four poles of attraction in the EU and two poles of attraction among OECD countries. The author also suggests that the presence of convergence clusters means the prospect of general income convergence is poor in both the EU and the OECD. Corrado et al. (2005) check for convergence clusters across EU regions by looking at gross value added per capita in the period 1975–99. Like Canova (2004), they suggest there is no single convergence process in the EU. Rather, there are diverse convergence paths across different sectors and parts of Europe, and the dynamics of regional convergence change over time. Additionally, the authors highlight the importance of geographical closeness for the sharing of convergence paths.

THE EMPIRICAL MODEL

TFP is an unobserved measure and there are several ways to quantify its level and growth. Since the different approaches for quantifying TFP each have their own advantages and disadvantages, the current study estimates the drivers of TFP growth with four separate methods of TFP calculation for comparison and robustness. The methods used to calculate TFP, briefly described below, are: the deterministic growth-accounting method or Solow residual approach; the Olley and Pakes (1996) control function method; the Greene (2005b) ‘true’ random effects (RE) stochastic frontier model; and a non-parametric data envelopment analysis (DEA) with the Malmquist productivity change index. These approaches to quantifying TFP are quite distinct in their assumptions and calculation or estimation mechanisms.

Growth-accounting approach for TFP growth determination

The deterministic growth-accounting framework based on the Solow residual assumes a general functional form of a log-linearized Cobb–Douglas production function. The growth rate of TFP in region i , $\Delta \ln A_{it}$, is given as:

$$\Delta \ln A_{it} = \ln \left(\frac{Y_{it}}{Y_{i,t-1}} \right) - (1 - \gamma) \ln \left(\frac{K_{it}}{K_{i,t-1}} \right) - \gamma \ln \left(\frac{L_{it}}{L_{i,t-1}} \right) \quad (1)$$

where Y_{it} and L_{it} are output in region i and year t in terms of GDP and the stock of the active labour force respectively. The capital stock K_{it} is calculated as:

$$K_{it} = (1 - \delta)K_{i,t-1} + I_{it},$$

where δ is depreciation; and I_{it} is investment. In line with standard empirical practice, the depreciation rate is equalized to 6% in the study. The initial stock of capital at the beginning of the observation period in the year 2000, $K_{i,2000}$, is evaluated as:

$$K_{i,2000} = I_{1,2001} / (g_i + \delta),$$

where g_i denotes the region's average trend growth rate in the Hodrick–Prescott-filtered investment series from the period 2001–07 using the smoothing parameter of $\lambda = 6.25$, in line with Ravn and Uhlig (2002). The parameter γ denotes the labour share in total output; and two TFP measures are calculated, one with γ set constant and equal to 0.67 in accordance with the previous literature (Gollin, 2002; Hsieh & Klenow, 2010; Vogel, 2015) and consistent evidence from the macroeconomic data for advanced economies, and the other with it as a country–year varying variable.¹

The TFP level for region i at year t , $\ln A_{it}$, is calculated using the geometric mean of the production inputs \bar{K}_t and \bar{L}_t and output \bar{Y}_t across all regions at year t :

$$\ln A_{it} = \ln \left(\frac{Y_{it}}{\bar{Y}_t} \right) - (1 - \gamma) \ln \left(\frac{K_{it}}{\bar{K}_t} \right) - \gamma \ln \left(\frac{L_{it}}{\bar{L}_t} \right) \quad (2)$$

The TFP gap is the relative difference between the TFP level in the frontier $TFP_{Ft} = \ln A_{Ft}$ and the particular region $TFP_{it} = \ln A_{it}$ given as:

$$TFP \text{ gap} = (TFP_{Ft} - TFP_{it}) / TFP_{Ft}$$

Olley and Pakes' (1996) control function approach for estimating TFP

The estimation of TFP is subject to bias if the positive correlation between the unobserved productivity shock and the observed level of inputs is ignored. The Olley and Pakes (1996) two-step procedure tackles this endogeneity problem by using investment as a proxy for productivity. Since investment is not monotonous at firm level, Levinsohn and Petrin (2003) modified the model by replacing investment with intermediate inputs as the proxy for a productivity shock. Akerberg, Caves, and Frazer (2015) noted for the model of Levinsohn and Petrin (2003), in particular, that the high collinearity between the labour input as the free variable and the intermediate input as the proxy variable of productivity prevents the parameters being identified in the first-stage estimation. The adjustment by Akerberg et al. (2015) introduces the proxy variable policy function to disentangle the productivity shock from output. A simulation study by Mollisi and Rovigatti (2017), however, shows that the correction by Akerberg et al. (2015) has serious deficiencies in empirical applications. Wooldridge (2009) introduced an alternative procedure for TFP estimation, which contributes in several respects. First, it replaces the two-step procedure with the GMM, which has easily attainable robust standard errors, and it removes the identification problem defined by Akerberg et al. (2015). Using the lags as instruments, however, reduces the sample size for the TFP estimation, and this is also a critical limitation in the current study. Given that most of the estimation problems addressed in the augmented and modified versions of Olley and Pakes (1996) refer back to a firm-level setting with non-monotonous investments and collinearity between free variables (typically labour) and the

productivity proxy, the current study based on regional data opts for the original two-step setting of Olley and Pakes (1996) with a Cobb–Douglas form:

$$y_{it} = \alpha + \mathbf{w}_{it}\beta + \mathbf{x}_{it}\gamma + \omega_{it} + \epsilon_{it} \quad (3)$$

where the investments, i_{it} , and the free variables, \mathbf{x}_{it} , proxy the productivity shock, ω_{it} , as $\omega_{it} = h(i_{it}, \mathbf{x}_{it})$.

This gives a partially linear model with a non-parametrical term:

$$\Phi_{it}(i_{it}, \mathbf{x}_{it}) = \mathbf{x}_{it}\gamma + h(i_{it}, \mathbf{x}_{it}) = \mathbf{x}_{it}\gamma + \omega_{it}$$

approximated by an n th-order polynomial, $\hat{\Phi}$:

$$y_{it} = \alpha + \mathbf{w}_{it}\beta + \mathbf{x}_{it}\gamma + h(i_{it}, \mathbf{x}_{it}) + \epsilon_{it} \quad (4)$$

After yielding the consistent estimator of β from (3) the γ and the productivity estimate $\hat{\omega}_{it} = \hat{\Phi}_{it} - \mathbf{x}_{it}\gamma$ derives from:

$$y_{it} - \mathbf{w}_{it}\hat{\beta} = \alpha_0 + \mathbf{x}_{it}\gamma + g(\hat{\Phi}_{it-1} - \mathbf{x}_{it-1}\gamma) + e_{it} \quad (5)$$

where the function $g(\cdot)$ is estimated non-parametrically. Olley and Pakes also introduce a third step for estimating the non-random attrition bias of firms, but this is obviously not a relevant consideration in the context of regions.

Greene's (2005b) 'true' random-effects stochastic frontier model

The stochastic frontier model with normal-half normal errors was first proposed by Pitt and Lee (1981):

$$y_{it} = \alpha + \mathbf{x}_{it}\beta + \epsilon_{it}$$

$$\epsilon_{it} = v_{it} - u_i \quad (6)$$

$$v_{it} \sim N(0, \sigma_v^2)$$

$$u_i \sim N^+(0, \sigma_u^2)$$

An extension with maximum likelihood estimation of time-varying inefficiency was proposed by Kumbhakar (1990) where the absence of time-varying technical efficiency can be tested with $\gamma = \delta = 0$:

$$u_{it} = g(t) \cdot u_i \text{ and } g(t) = [1 + \exp(\gamma t + \delta t^2)]^{-1} \quad (7)$$

A similar 'time-decay' model by Battese and Coelli (1992) defines time-varying function as:

$$g(t) = \exp[-\gamma(t - T_i)],$$

where T_i denotes the number of available time observations.

However, both these time-varying stochastic frontier models fail to separate the time in-variant unit-specific unobserved heterogeneity from the inefficiency and, hence, produce biased efficiency

estimates. Greene (2005a) proposed a solution introducing unit-varying intercepts, α_i , instead of a common intercept, α , which enables time-varying efficiency and time-invariant unit-specific heterogeneity to be accounted for separately:

$$y_{it} = \alpha_i + \mathbf{x}_{it}\beta + \epsilon_{it} \quad (8)$$

Depending on the assumptions about the correlation between the error term and the time-invariant term α_i , the model is estimated in a fixed- or random-effect framework. The estimation with the fixed-effects assumption is, however, problematic in short panels with a large number of units (N) and a small time dimension (T). Given this limitation, the current study opts to use the Greene (2005b) ‘true’ random-effects model.

Data envelopment analysis (DEA) with the Malmquist productivity change index

Like stochastic frontier analysis, DEA does not presume that production is efficient, but neither does it require any underlying functional form for production such as Cobb–Douglas, translog or any other, in the same way as the growth-accounting framework, the Olley–Pakes method or stochastic frontier analysis (Färe et al., 1994). The Malmquist productivity change index relies on distance functions, which measure the raw distance between a given level and the maximal potential output level. The distance function for region, r , is defined as:

$$D_r^t(x_r^{t+1}, y_r^{t+1}) = (\sup \theta: (x_r^{t+1}, y_r^{t+1}\theta) \in S(t))^{-1} \quad (9)$$

The output-oriented Malmquist TFP change index between period t and $t + 1$ under constant returns to scale (CRS) is:

$$M_r^{t+1}(x_r^{t+1}, y_r^{t+1}, x_r^t, y_r^t) = \left[\frac{D_r^t(x_r^{t+1}, y_r^{t+1})}{D_r^t(x_r^t, y_r^t)} \times \frac{D_r^{t+1}(x_r^{t+1}, y_r^{t+1})}{D_r^{t+1}(x_r^t, y_r^t)} \right]^{1/2} \quad (10)$$

Like the stochastic frontier approach, the Malmquist index contains and disentangles two aspects of productivity change: the change in production efficiency and the rate of technological progress:

$$M_r^{t+1}(x_r^{t+1}, y_r^{t+1}, x_r^t, y_r^t) = \underbrace{\frac{D_r^{t+1}(x_r^{t+1}, y_r^{t+1})}{D_r^t(x_r^t, y_r^t)}}_{\text{Efficiency Change}} \times \underbrace{\left[\frac{D_r^t(x_r^{t+1}, y_r^{t+1})}{D_r^{t+1}(x_r^{t+1}, y_r^{t+1})} \times \frac{D_r^t(x_r^t, y_r^t)}{D_r^{t+1}(x_r^t, y_r^t)} \right]^{1/2}}_{\text{Technological Progress}} \quad (11)$$

The sample size for regressions based on the Malmquist index is smaller, since the outlier detection by Simar (2003) is applied. Consequently, the regions of Spain and France drop out from the sample of advanced regions, while Malta and the regions of Hungary drop out from the emerging Europe sample. The number of regions in the overall sample drops from 99 in the baseline regression to 77. Despite the reduced sample size, the results remain qualitatively similar and corroborate the baseline findings. It must still be remembered that unlike the growth-accounting calculation used to find TFP growth, the Malmquist productivity change index does not assume technological efficiency and the TFP growth it finds contains not only the effect of technical efficiency but also the effect of technological change or technical progress or regress. Calculating the Malmquist index with DEA

requires a balanced panel, which led to a reduction in the sample size to 596 observations from 77 regions in 27 countries, with 56 advanced and 21 emerging regions.

Estimation of the drivers of TFP growth

The drivers of TFP growth are investigated by regressing the TFP gap, R&D expenditures and human capital endowments along with their interactions on the measures of TFP growth calculated using the four separate methods. More precisely, the study encompasses the change in the human capital endowment of the regions ($\Delta HC_{i,t-1}$), the log of real R&D expenditures per capita ($RD_{i,t-1}$), deflated with respect to the year 2000 as the base, and the initial TFP gap in 2003 ($GAP2003_i$), which is one year before the major EU enlargement of 2004. Additionally, a regional spillover or regional convergence variable ($REG_{it} = W \cdot TFP_{it}^+$) is generated, which employs the spatial $N \times N$ multidimensional weight matrix of N regions, W , containing inverse Euclidean distances² multiplied by the positive values of the TFP level of the regions. In addition, the model incorporates cyclical effects by introducing dummies for the periods 2000–03, 2004–07, 2008–10 and 2011–13, with the first two periods forming the reference categories. The region fixed effects, including the institutional heterogeneities of the regions, are captured with the time-invariant unobserved variable α_i :

$$\begin{aligned}
 TFP\ growth_{it} = & \beta_0 + \beta_1 TFP\ growth_{i,t-1} \\
 & + \beta_2 TFP\ gap_{gi,t-1} + \beta_3 \Delta HC_{i,t-1} \\
 & + \beta_4 RD_{i,t-1} + \beta_5 \Delta HC_{i,t-1} \\
 & \times TFP\ gap_{gi,t-1} + \beta_6 RD_{i,t-1} \\
 & \times TFP\ gap_{gi,t-1} + \beta_7 GAP2003_i \\
 & + \beta_8 REG_{it} + \beta_{9,2009-2010} \\
 & + \beta_{10,2011-2013} + \alpha_i + \epsilon_{it}
 \end{aligned} \tag{12}$$

DATA AND METHODOLOGY

The empirical analysis uses NUTS-1-level regional data to maximize the coverage of heterogeneous regions across Europe to ensure cross-sectional variety in TFP growth and levels, and to avoid sample selection or attrition bias caused by missing data at more detailed regional levels. Moreover, since one of the main variables of interest is R&D expenditure and R&D is typically concentrated and prevalent in more developed or more populated regions, the NUTS-1 level allows for better comparability of regions and avoids gaps and discontinuities in the R&D measure. The study sample contains NUTS-1-level regions from 31 countries, 28 of which are current EU member states, while the other three (Iceland, Norway and Switzerland) are European Free Trade Association (EFTA) members. All the NUTS-1 level regions of the EU are included in the sample, except for the Azores region of Portugal (Região Autónoma dos Açores) and the French overseas territories (Départements d'Outre-Mer), which were omitted because of missing data (see Appendix C for a list of the EU regions by country). Country borders for the three EFTA members overlap with the NUTS-1-level regional borders, and this is also the case with several smaller EU members. In total the sample contains 99 European NUTS-1 regions. In the further analysis, two regional subsamples are defined, which are the subsample of advanced economies, containing the 15 older EU member states plus the three EFTA countries, and the emerging Europe subsample, which contains the newer member states that joined the EU in 2004 or later. The time frame of the study spans from the year 2000 to 2013, and it uses annual data retrieved from the EUROSTAT regional statistics.

Three indicators are used to calculate TFP growth. First, the GDP of the region is used as a proxy for output. Second, the number of people employed, covering both employees and the self-employed, is taken as labour. Third, investments in capital stock, or gross fixed capital formation, are used to calculate the capital stock in a given period using the growth-accounting methodology. Like Rodríguez-Pose and Crescenzi (2008), we compose the human capital measure by using principal component analysis. The baseline human capital measure is comprised of two variables: (1) the percentage of the population aged 25–64 years with tertiary education; and (2) the percentage of people aged 25–64 years who have participated in lifelong education or training within the last four weeks. The level of human capital is calculated as the first principal component of these two variables, explaining 78% of the total variation (Table 1). The variable of tertiary education receives a weight of 0.637 and the lifelong learning variable a weight of 0.771. An alternative measure of human capital was calculated for robustness purposes by adding the percentage of R&D employees and scientists within the active population as a third variable in the principal component analysis to capture the quality of the region’s human capital endowment (Table 1 and see Appendix B). Adding the variable for R&D employees had a small effect on the composition and variation captured by the first two principal components. The logarithm of real gross domestic expenditure on R&D per capita in euros is used to measure the impact of each region’s contribution to R&D.

Table 1. Principal component (PC) results (coefficients) for human capital (HC) variables.

Variable	Baseline human capital		Alternative human capital	
	PC1	PC2	PC1	PC2
Population aged 25–64 years with a tertiary education (%)	0.6368	0.7710	0.5562	0.8310
Population aged 25–64 years in lifelong learning (%)	0.7710	0.6368	0.8304	–0.5563
Research and development (R&D) employees and scientists from the active population (%)			0.032	–0.007
Eigenvalue	95.644	27.513	95.534	23.551
Cumulative variation	0.777	1.000	0.8011	0.9986

Source: Authors’ calculations based on EUROSTAT data.

The distribution of the main variables as averages over the period 2000–13 for the overall sample of the European NUTS-1 regions is illustrated in Figure 1. During this period, most of the fastest growing regions were in Eastern Europe. The highest rate of average TFP growth over the sample period was attained by a Romanian region, Macroregiunea Trei (top left-hand map in Figure 1). However, negative annual average TFP growth was registered in multiple, mainly advanced, regions. The regions with the highest levels of TFP vary across the years and across different methods for calculating TFP, but the most dominant are the London region, Luxembourg, Île-de-France, Berlin and Norway, which is never treated as a frontier region because of its specific features as an oil-producing country (top right-hand map in Figure 1). Conversely, the emerging regions of Europe had the highest TFP gap to the frontier. The average spending on R&D per inhabitant³ is shown in the bottom left-hand panel in Figure 1. Advanced regions invested the most in research, while the regions of emerging Europe spent comparatively little. The biggest spender was Eastern Sweden (Östra Sverige), which invested on average €1623 annually per inhabitant on R&D in nominal terms, while the average nominal spending across the regions in the period 2000–13 was €430 per inhabitant. The region with the highest average level of human capital over the sample period was London, which was closely followed by Switzerland (bottom right-hand panel in Figure 1). High average levels of human capital could also be found in the Nordic countries and other regions of the UK, while the lowest average levels of human capital were recorded in three Romanian regions.

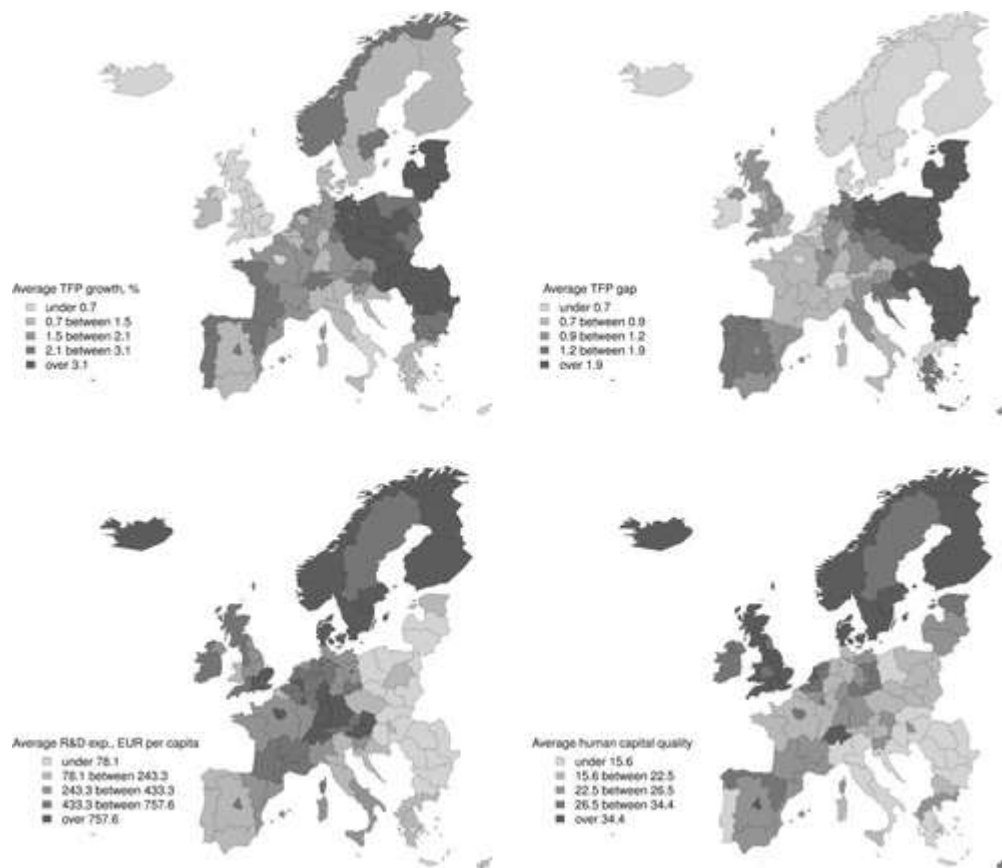


Figure 1. Regional total factor productivity (TFP), research and development (R&D) and human capital indicators: averages, 2000–13.
Source: EUROSTAT.

The study does not use all the possible lags as instruments, which is common practice in empirical or finite-sample studies as doing so would deteriorate the finite sample behaviour, so the number of lags is restricted to instruments for the first-difference equation.⁴

The study uses the underlying panel-data structure to address the main econometric issues that emerge in the design, such as unobserved effects, heterogeneity and reverse-causality problems, and it comes up with consistent parameter estimates. The baseline results are derived from the system GMM estimator of Arellano and Bover (1995) and Blundell and Bond (1998). The GMM estimator has several merits, as first it can cope with unobserved time-invariant or time-persistent regional heterogeneity such as a region's cultural, historical or demographic features; second, it accounts for the endogeneity bias arising from the correlation between the lagged dependent variable and error term or between the explanatory variables and the error term; and third, given the heteroskedastic error terms, the GMM estimator is also an asymptotically efficient estimator when compared with two-stage least squares (2SLS) since it employs information from the variance–covariance matrix of moments. As proof of the validity of the GMM specification, the coefficient estimate of the lagged autoregressive term from the pooled ordinary least squares (OLS) and from the fixed-effects panel estimator are given under model diagnostics. For an accurate GMM specification, the estimate of the lagged autoregressive parameter should assume a value lower than the upward biased OLS estimate and higher than the downward biased fixed-effects estimate. The GMM assumes a linear functional relationship between the variable of interest and the regressors, and allows the target variable to have a dynamic structure depending on its own past realizations. The standard errors are corrected for downward bias in small samples (Windmeijer, 2005) and collapsed instruments are used to avoid instrument proliferation, as suggested

by Roodman (2009). To escape data loss in the finite sample due to observational gaps, the study uses orthogonal deviation transformation instead of first differences to remove time-invariant unobserved effects. Cyclical dummies are introduced to reduce possible correlation across idiosyncratic disturbances in regions.

RESULTS AND DISCUSSION

The main expectations are confirmed by the baseline estimation results for all the regions covered (Table 2). The autoregressive term for TFP growth enters the model with a negative sign and is significant across all the estimations except for the Olley and Pakes (1996) specification. This reflects a volatility correction mechanism, or a mean-reverting growth path where the high-growth years are followed by lower growth periods and vice versa. The convergence effect is manifested in a positive and statistically significant TFP gap, and this effect is again missing only for the Olley and Pakes specification. The TFP gap main effect shows how TFP growth is affected if there is no increase in human capital or in R&D spending. The main effects for human capital and R&D expenditures are found to be positive and they can be interpreted as effects at the productivity frontier, equivalent to a zero TFP gap. The human capital endowment has a dominating positive effect on TFP growth, whereas there is only weak similar evidence for R&D expenditures and it is significant in only two of five estimations. The regional, or spatial, productivity spillover effects are significant and comparable in magnitude across all five estimations using fundamentally distinct methods of calculating TFP, corroborating earlier studies that note the significance of the spatial dimension for productivity growth (e.g., Beugelsdijk et al., 2017; Cuaresma et al., 2014; Funke & Niebuhr, 2005; Varga & Schalk, 2004). The initial level of the TFP gap for 2003 is also consistently negative and significant in four of five estimates, showing the adverse effect of the weak starting level on further productivity convergence and implying strong path dependencies. This finding indicates there might be a critical level of capacity needed for sustained improvement in TFP and that countries falling below that threshold cannot keep up with the pace of TFP growth. Rodríguez-Pose and Crescenzi (2008), using the initial level of GDP per capita, provide similar evidence, and the importance of historical development paths for current TFP levels in European regions is also stressed by Beugelsdijk et al. (2017). The cyclical effect has been controlled for with period dummies for the turbulent years around the global financial crisis of 2008–10 and the post-crisis recovery years of 2011–13. The estimation outcomes confirm the intuition of a productivity drop in the crisis years of 2008–10 and a positive recovery in the period 2011–13.

Table 2. Total factor productivity (TFP) growth estimations with TFP–gap interactions, total sample, 2003–13.

	GA, constant γ	GA, varying γ	Olley–Pakes	Greene, RE	DEA
L.TFP growth	-0.198*** -0.052	-0.191*** -0.055	-0.090 -0.09	-0.233*** -0.057	0.203*** -0.051
L.TFP GAP	0.195*** -0.042	0.142** -0.069	-0.011 -0.101	0.267*** -0.072	0.409*** -0.132
L.log R&D	0.030*** -0.011	0.012 -0.013	-0.008 -0.023	0.015 -0.011	0.019* -0.01
LD.HC	0.567*** -0.118	0.501*** -0.098	0.028 -0.105	0.486*** -0.136	0.466*** -0.113
L.R&D*GAP	-0.013** -0.006	-0.004 -0.011	0.019 -0.023	-0.008 -0.011	-0.044 -0.029
LD.HC*GAP	-0.012	-0.034*	0.012	-0.001	-0.008

	-0.014	-0.018	-0.019	-0.016	-0.017
2008–2010	-0.041***	-0.045***	-0.008*	-0.032***	0.051***
	-0.005	-0.006	-0.004	-0.007	-0.007
2011–2013	0.010*	-0.004	0.064***	0.005	0.022***
	-0.006	-0.005	-0.01	-0.007	-0.008
D.spillover	0.046***	0.050***	0.092***	0.038***	0.044***
	-0.011	-0.011	-0.023	-0.014	-0.011
					-
GAP2003	-0.085***	-0.085***	-0.029	-0.143***	0.102**
	-0.021	-0.022	-0.028	-0.05	-0.047
					-
Intercept	-0.180***	-0.080	-0.007	-0.093	0.121***
	-0.065	-0.071	-0.111	-0.06	-0.04
AR_OLS	-0.154	-0.147	-0.070	-0.155	-0.055
AR_FE	-0.209	-0.193	-0.175	-0.276	-0.200
Hansen	95.034	97.267	97.101	97.24	76.236
<i>p</i> -Hansen	0.311	0.258	0.261	0.136	0.83
AR1	-5.003	-4.860	-4.006	-4.509	-5.231
<i>p</i> -AR1	0	0	0	0	0
AR2	0.442	0.398	-0.363	-0.105	1.373
<i>p</i> -AR2	0.659	0.691	0.716	0.917	0.17
<i>F</i>	16.756	19.287	13.175	18.355	20.42
<i>p</i> - <i>F</i>	0	0	0	0	0
<i>J</i>	100	100	100	94	100
<i>N</i>	766	766	766	742	618
<i>N</i> -region	99	99	99	99	77
<i>N</i> -country	31	31	31	31	27

Notes: The dependent variable is TFP growth. Values are Windmeijer finite-sample corrected standard errors.

AR_OLS denotes the autoregressive term from the pooled ordinary least squares (OLS); AR_FE denotes the autoregressive term from the fixed-effects panel estimator.

γ denotes the labour share in total output and is set constant and equal to 0.67 in the 'GA, constant γ model' and is varying in time and across countries in the 'GA, varying γ model'.

DEA, data envelopment analysis; GA, growth accounting; RE, random effects.

***, **, *Statistically significant at the 1%, 5% and 10% levels respectively.

Source: Authors' calculations on EUROSTAT data.

The study demonstrates noteworthy differences in the drivers of TFP between the advanced and emerging European regions (Figure 2 and see Tables A1 and A2 in Appendix A). It should be noted, however, that since the CEE sample is smaller, the effects from it are less precisely estimated. While the positive human capital effect is present in three of four estimations for the advanced European regions and increases slightly as distance to the TFP frontier increases, a similar effect is marginally significant in only two of four estimates for the CEE sample, and it decreases slightly as distance to the TFP frontier increases. This implies that the positive effect of human capital endowment on TFP growth is more evident in the advanced regions of Europe, where the convergence trend in regions further from the productivity frontier appears to have a stronger positive human capital effect on TFP growth than is the case in regions closer to the frontier. However, contradictory evidence is found in the emerging Europe subsample, where the positive human capital effect on TFP growth decreases with the distance to the

TFP frontier. This finding might indicate that institutional deficiencies prevail in emerging Europe, where they hamper the positive effect of human capital on TFP growth at low TFP levels. Also, R&D expenditures have opposite implications for the advanced and emerging regional subsamples, though the effect remains insignificant for the larger part of the TFP gap distribution. In any case, the results (see Figure 2(a)) indicate that while R&D expenditures in advanced regions only have a significant positive effect on TFP growth in the regions most distant from the productivity frontier, any similar positive effect is only apparent for the most productive regions in emerging Europe. This evidence shows that while the marginal return on human capital and R&D is decreasing in advanced regions and less productive regions gain relatively more from increases in human capital and R&D, the contrary is true for the CEE subsample, where only the most productive regions gain from an increase in human capital endowment and from investment in R&D. Regional convergence in advanced Europe and regional divergence in emerging Europe have been documented by Sokol (2001) and more recently by Cuaresma et al. (2014) who find that income convergence between European countries is mainly driven by the catching-up process in CEE, while convergence within countries is primarily observed in older EU member states.

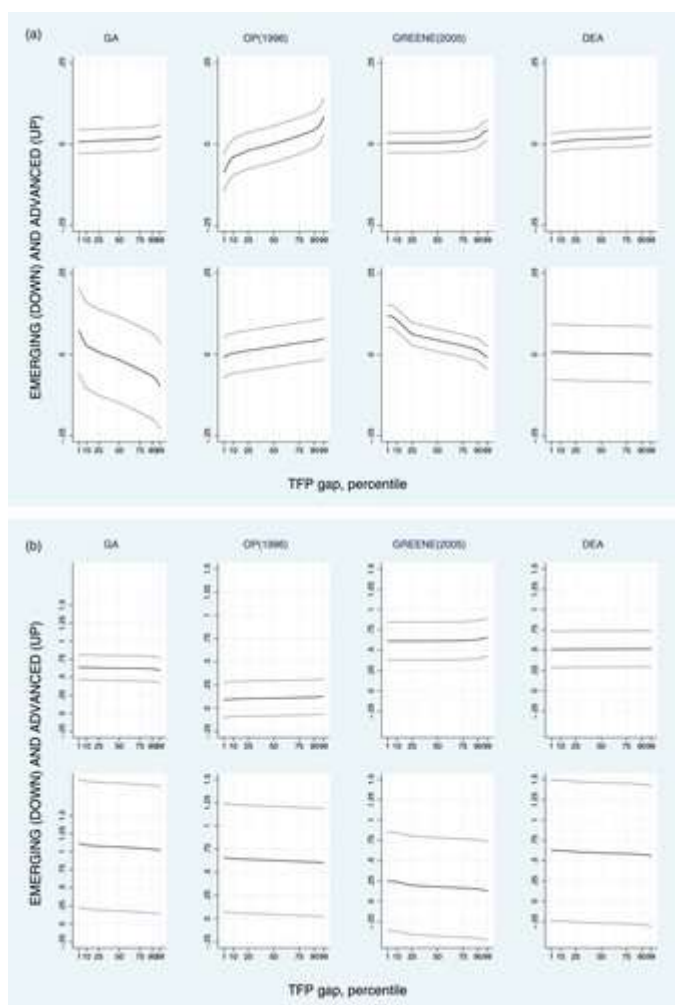


Figure 2. (a) Research and development (R&D), marginal effect on total factor productivity (TFP) growth (%) with 90% confidence intervals (CI); and (b) human capital, marginal effect on TFP growth (%) with 90% CI.

CONCLUSIONS

The study aimed to estimate the TFP growth factors across a heterogeneous sample of European regions during the era of intense European integration in the period 2000–13. Following the pan-European results, the sample was disentangled into a group of advanced regions in the EU-15 and EFTA and a group of emerging EU-13 regions. The pooled results confirm that TFP growth is affected by the human capital endowment of the regions, but much less so by their commitment to R&D spending, and that both effects vary depending on the current productivity level of the region. Several notable implications appear from interaction effects between the TFP gap and human capital endowment and R&D investments. When comparing the results between the advanced and emerging groups, it becomes apparent that while the positive human capital and R&D effects increase in the TFP gap for the advanced regions, they decrease in the TFP gap for the emerging regions of Europe. This might imply that institutions in the low TFP regions in the emerging EU-13 are underdeveloped, preventing human capital and R&D having their full positive effect, while in advanced regions the increase in human capital and R&D help regions that lag behind in TFP to catch up. This evidence is further corroborated by the significant negative effect of the initial lag in TFP, the TFP gap in 2003, in the pooled estimation. This result is an indication of path dependency and of a critical minimum start-up level that allows a region to keep up with the TFP growth race. Overall, the study finds strong spillover and convergence effects across regions and over time and more strongly so in the pooled sample of regions, which indicates that the positive spillovers mainly emerge among more heterogeneous regions.

Using a heterogeneous sample of the European regions, the study demonstrates the varying paths of TFP growth at different levels of economic development. The results are in agreement with the theoretical propositions of Funke and Strulik (2000) and with recent empirical evidence provided by Capello and Lenzi (2015) and Marrocu et al. (2011). The main contribution of this paper is that it accounts for the time-dynamic convergence in the TFP gap and for the cross-regional spillovers in a modern econometric framework considering the self-reinforcing feedback effects between productivity growth, human capital and R&D. Furthermore, it highlights that the effects of human capital endowment and R&D investment are heterogeneous, depending on the prevailing productivity gap across advanced and emerging regions of Europe. The underlying TFP measure is calculated with four distinct methods, which adds to the reliability of the results. While the results cast a light on new aspects of TFP growth patterns and corroborate the evidence for dual-growth pathways in Europe, however we still lack any deeper insight into the specific components of the absorptive capacity of regions and the prevailing economic structures that would let one understand better the mechanisms through which their interaction generates productivity growth.

Several policy implications arise from this study. First, as the results indicate that the impact of spatial productivity spillovers is significant, it is important to connect the peripheral regions of Europe better with the high-productivity core regions. Beyond traditional means such as better transport connections, deeper interregional connectedness through digital channels could reduce geographical barriers notably. As such, the EU's initiative to promote the digital single market is commendable. Second, this study observes a tendency towards regional divergence in the CEE, stressing the importance of focusing on productivity gaps both within and between countries when combating disparities. Finally, we note that investments in human capital and R&D yield lower returns in regions that fall farther behind the technology frontier, possibly implying institutional deficiencies that prevent investments from having their full positive effect. Indeed, a highly educated workforce on its own is not much use if the workers cannot adequately use their knowledge and skills. Although there is no simple solution for improving imperfect institutions, policies that encourage an open, competitive and transparent business environment are likely to be beneficial.

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NOTES

1. Brada (2013) observes systematic variation in the labour share in developed and developing countries over the post-Second World War period and stresses its significance in explaining economic growth. We account for the time-varying labour share by conducting a robustness check using the NUTS-1-level regional statistics on employee compensation from EUROSTAT and the labour-share statistics at the country level from The Conference Board Total Economy Database, May 2015 (<http://www.conference-board.org/data/economydatabase/>) (see Appendix B).
2. The Euclidean distance measures the multivariate proximity between the two regions considering the geographical latitude and longitude and the country membership of the particular region. Accordingly, regions located at a shorter geographical distance or within the same country have a higher inverse Euclidean distance weight.
3. Econometric estimations use the log of annual R&D investments per capita in real terms.
4. The lagged levels might be weak instruments for the first-difference equation and, hence, many authors skip the longer lags in empirical applications. All regressors are instrumented with their lags except for the regional spillover effects, the TFP gap in 2003 and cyclical dummies.

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APPENDIXES

Appendix A: TFP growth estimations by advanced and emerging European regions

Table A1. TFP growth estimations with TFP-Gap interactions, advanced regions, 2003-2013

	GA, constant γ	GA, varying γ	Olley-Pakes	Greene, RE	DEA
L.TFP growth	-0.151*** (0.053)	-0.121** (0.051)	0.128 (0.130)	-0.086* (0.048)	-0.105 (0.082)
L.TFP GAP	0.063 (0.101)	0.064 (0.089)	-0.695*** (0.254)	-0.155 (0.164)	-0.015 (0.348)
L.log R&D	0.004 (0.015)	0.008 (0.016)	-0.142*** (0.053)	0.004 (0.009)	0.003 (0.029)
LD.HC	0.651*** (0.103)	0.637*** (0.094)	0.074 (0.123)	0.613*** (0.132)	0.508*** (0.127)
L.R&D*GAP	0.005 (0.015)	0.007 (0.013)	0.148*** (0.050)	0.039 (0.025)	0.031 (0.066)
LD.HC*GAP	-0.032* (0.019)	-0.014 (0.014)	0.036** (0.015)	0.041** (0.017)	0.013 (0.017)
2008-2010	-0.027*** (0.006)	-0.026*** (0.006)	0.007 (0.007)	-0.004 (0.003)	-0.030*** (0.007)
2011-2013	0.001 (0.008)	-0.001 (0.007)	0.031** (0.012)	0.019*** (0.006)	0.030*** (0.009)
D.spillover	0.066*** (0.013)	0.070*** (0.012)	0.091*** (0.029)	0.018 (0.012)	0.049*** (0.017)
GAP2003	-0.064 (0.043)	-0.069** (0.034)	-0.054 (0.043)	0.007 (0.054)	-0.060 (0.037)
Intercept	-0.034 (0.089)	-0.063 (0.091)	0.730** (0.295)	-0.049 (0.051)	-0.054 (0.161)
AR_OLS	-0.151	-0.118	0.096	-0.118	-0.029
AR_FE	-0.208	-0.194	-0.068	-0.234	-0.205
Hansen	71.918	70.817	68.312	71.301	55.532
p-Hansen	0.349	0.384	0.467	0.221	0.861
AR1	-3.974	-3.887	-3.172	-3.943	-4.095
p-AR1	0.000	0.000	0.002	0.000	0.000
AR2	-0.961	-0.921	-1.753	-0.876	-0.699
p-AR2	0.337	0.357	0.080	0.381	0.484
F	14.049	16.284	23.474	8.494	16.505
p-F	0.000	0.000	0.000	0.000	0.000

N	79	79	79	74	79
N	547	547	547	529	426
N-region	75	75	75	75	56
N-country	18	18	18	18	15

Source: Authors' calculations on Eurostat data.

Note: Dependent variable is TFP growth. Windmeijer finite sample corrected standard errors.

AR_OLS denotes the autoregressive term from the pooled OLS and AR_FE denotes the autoregressive term from the fixed effects panel estimator.

γ denotes the labour share in total output and is set constant and equal to 0.67 in the "GA, constant γ model" and is varying in time and across countries in the "GA, varying γ model".

***, **, * stand for 1%, 5% and 10% level statistical significance respectively

Table A2. TFP growth estimations with TFP-Gap interactions, CEE regions, 2003-2013

	GA, constant γ	GA, varying γ	Olley-Pakes	Greene, RE	DEA
L.TFP growth	-0.181 (0.151)	-0.205 (0.157)	-0.331* (0.164)	-0.352*** (0.103)	-0.237* (0.128)
L.TFP GAP	0.061 (0.118)	0.473 (0.354)	-0.030 (0.182)	0.548** (0.257)	0.298 (0.408)
L.log R&D	-0.062 (0.089)	0.162 (0.165)	-0.048 (0.081)	0.120 (0.074)	0.007 (0.034)
LD.HC	0.551 (0.432)	1.166* (0.629)	0.697** (0.334)	0.249 (0.342)	0.627 (0.520)
L.R&D*GAP	0.042 (0.048)	-0.128 (0.118)	0.066 (0.074)	-0.102 (0.071)	-0.014 (0.122)
LD.HC*GAP	0.024 (0.091)	-0.073 (0.084)	-0.064 (0.059)	-0.095*** (0.034)	-0.115* (0.060)
2008-2010	-0.056** (0.021)	-0.077*** (0.016)	-0.029* (0.016)	-0.085*** (0.021)	-0.082*** (0.017)
2011-2013	-0.013 (0.024)	-0.057** (0.026)	0.064*** (0.021)	0.000 (0.017)	-0.021 (0.013)
D.spillover	0.003 (0.026)	0.023 (0.034)	0.082** (0.035)	0.057*** (0.018)	0.018 (0.012)
GAP2003	-0.089 (0.054)	-0.022 (0.064)	-0.097 (0.074)	-0.072 (0.086)	-0.054 (0.093)
Intercept	0.079 (0.243)	-0.571 (0.484)	0.049 (0.191)	-0.430 (0.274)	-0.084 (0.079)
AR_OLS	-0.149	-0.193	-0.327	-0.263	-0.179
AR_FE	-0.216	-0.202	-0.359	-0.361	-0.266
Hansen	20.062	21.494	22.350	20.932	17.819
p-Hansen	0.828	0.490	0.719	0.789	0.717
AR1	-2.937	-2.905	-2.486	-3.092	-3.166
p-AR1	0.003	0.004	0.013	0.002	0.002
AR2	0.422	0.596	0.604	0.622	1.255
p-AR2	0.673	0.551	0.546	0.534	0.209
F	14.150	5.057	9.778	19.767	6.371
p-F	0.000	0.001	0.000	0.000	0.000

J	38	33	38	38	33
N	219	219	219	213	192
N-region	24	24	24	24	21
N-country	13	13	13	13	12

Source: Authors' calculations on Eurostat data.

Note: Dependent variable is TFP growth. Windmeijer finite sample corrected standard errors.

AR_OLS denotes the autoregressive term from the pooled OLS and AR_FE denotes the autoregressive term from the fixed effects panel estimator.

γ denotes the labour share in total output and is set constant and equal to 0.67 in the "GA, constant γ model" and is varying in time and across countries in the "GA, varying γ model".

***, **, * stand for 1%, 5% and 10% level statistical significance respectively.

Appendix B: Robustness Check Estimations with alternative human capital measure

This section presents the estimations done as a robustness check with an alternate definition of human capital endowment based on principal component analysis with three variables: the percentage of the population with tertiary education, the percentage of the population in lifelong learning, and R&D employees and scientists within the active population (see Table 1). It might be possible that TFP is driven not only by improved levels of academic or occupational training, but also by the presence of front-line knowledge in science and research, and that it is necessary to account for this to complement the human capital measure. The robustness estimations reveal that the results remain qualitatively the same when the alternate measure of human capital is employed, which further validates the main findings of the study.

Table B1. TFP growth estimations with TFP-Gap interactions with alternative human capital, Total Sample, 2003-2013

	GA, constant γ	GA, varying γ	Olley-Pakes	Greene, RE	DEA
L.TFP growth	-0.228*** (0.052)	-0.218*** (0.053)	-0.137 (0.090)	-0.232*** (0.076)	-0.274*** (0.048)
L.TFP GAP	0.210*** (0.048)	0.077 (0.072)	0.010 (0.101)	0.382*** (0.107)	0.468*** (0.164)
L.log R&D	0.030** (0.013)	-0.006 (0.014)	-0.001 (0.024)	0.020 (0.013)	0.017 (0.010)
LD.HC	0.452*** (0.106)	0.367*** (0.112)	-0.021 (0.120)	0.665*** (0.144)	0.375*** (0.092)
L.R&D*GAP	-0.018*** (0.006)	0.006 (0.012)	0.010 (0.024)	-0.023 (0.017)	-0.060* (0.033)
LD.HC*GAP	-0.018 (0.014)	-0.040** (0.017)	0.009 (0.021)	0.002 (0.025)	-0.067*** (0.023)
2008-2010	-0.047*** (0.005)	-0.052*** (0.006)	-0.012** (0.005)	-0.029*** (0.007)	-0.060*** (0.007)
2011-2013	-0.001 (0.006)	-0.013*** (0.005)	0.060*** (0.010)	0.003 (0.009)	0.007 (0.006)
D.spillover	0.036*** (0.013)	0.048*** (0.011)	0.088*** (0.025)	0.033** (0.015)	0.036*** (0.010)
GAP2003	-0.089*** (0.023)	-0.079*** (0.021)	-0.017 (0.024)	-0.195*** (0.061)	-0.086 (0.053)
Intercept	-0.161** (0.079)	0.026 (0.079)	-0.027 (0.116)	-0.126* (0.070)	-0.099** (0.038)
AR_OLS	-0.161	-0.158	-0.088	-0.154	-0.091
AR_FE	-0.229	-0.202	-0.181	-0.315	-0.232
Hansen	92.526	93.985	95.409	94.984	74.891
p-Hansen	0.378	0.338	0.302	0.174	0.857
AR1	-4.908	-4.844	-3.958	-4.182	-5.177
p-AR1	0.000	0.000	0.000	0.000	0.000
AR2	-0.095	0.144	-0.480	-0.184	0.743
p-AR2	0.924	0.886	0.631	0.854	0.457
F	16.292	18.782	14.252	26.604	16.008
p-F	0.000	0.000	0.000	0.000	0.000

J	100	100	100	94	100
N	701	701	701	677	553
N-region	98	98	98	98	76
N-country	30	30	30	30	26

Source: Authors' calculations on Eurostat data.

Note: Dependent variable is TFP growth. Windmeijer finite sample corrected standard errors.

AR OLS denotes the autoregressive term from the pooled OLS and AR FE denotes the autoregressive term from the fixed effects panel estimator.

γ denotes the labour share in total output and is set constant and equal to 0.67 in the "GA, constant γ model" and is varying in time and across countries in the "GA, varying γ model".

***, **, * stand for 1%, 5% and 10% level statistical significance respectively.

Table B2. TFP growth estimations with TFP-Gap interactions with alternative human capital, Advanced regions, 2003-2013

	GA, constant γ	GA, varying γ	Olley-Pakes	Greene, RE	DEA
L.TFP growth	-0.157*** (0.051)	-0.094* (0.047)	-0.036 (0.091)	-0.022 (0.113)	-0.136 (0.082)
L.TFP GAP	0.199* (0.111)	0.047 (0.080)	-0.722*** (0.257)	-0.414*** (0.070)	-0.253 (0.512)
L.log R&D	0.017 (0.017)	-0.002 (0.017)	-0.159*** (0.046)	-0.005 (0.007)	-0.003 (0.038)
LD.HC	0.493*** (0.093)	0.449*** (0.076)	0.059 (0.144)	0.505** (0.244)	0.938*** (0.198)
L.R&D*GAP	-0.026 (0.017)	0.002 (0.010)	0.140*** (0.048)	0.062*** (0.016)	0.074 (0.092)
LD.HC*GAP	-0.011 (0.016)	0.000 (0.013)	0.026 (0.022)	0.169*** (0.056)	0.050 (0.031)
2008-2010	-0.033*** (0.007)	-0.030*** (0.006)	-0.006 (0.006)	-0.012 (0.013)	-0.003 (0.009)
2011-2013	-0.005 (0.007)	-0.010 (0.008)	0.035*** (0.013)	0.011** (0.004)	0.035*** (0.009)
D.spillover	0.074*** (0.018)	0.088*** (0.022)	0.089*** (0.032)	0.006 (0.015)	0.037 (0.026)
GAP2003	-0.044 (0.041)	-0.038 (0.033)	-0.021 (0.033)	0.135** (0.066)	-0.044 (0.064)
Intercept	-0.091 (0.101)	0.007 (0.097)	0.860*** (0.252)	0.005 (0.043)	-0.046 (0.206)
AR_OLS	-0.152	-0.123	0.074	-0.053	-0.072
AR_FE	-0.220	-0.204	-0.089	-0.158	-0.244
Hansen	69.951	68.650	68.516	72.369	53.827
p-Hansen	0.881	0.902	0.928	0.791	0.997
AR1	-4.044	-3.811	-3.391	-3.067	-3.977
p-AR1	0.000	0.000	0.001	0.002	0.000
AR2	-1.264	-1.081	-1.684	-0.490	-2.555
p-AR2	0.206	0.280	0.092	0.624	0.011
F	9.517	11.534	17.777	28.270	10.751
p-F	0.000	0.000	0.000	0.000	0.000

J	96	96	98	94	96
N	487	487	487	469	366
N-region	74	74	74	74	55
N-country	17	17	17	17	14

Source: Authors' calculations on Eurostat data.

Note: Dependent variable is TFP growth. Windmeijer finite sample corrected standard errors.

AR_OLS denotes the autoregressive term from the pooled OLS and AR_FE denotes the autoregressive term from the fixed effects panel estimator.

γ denotes the labour share in total output and is set constant and equal to 0.67 in the "GA, constant γ model" and is varying in time and across countries in the "GA, varying γ model".

***, **, * stand for 1%, 5% and 10% level statistical significance respectively

Table B3. TFP growth estimations with TFP-Gap interactions with alternative human capitals, CEE regions, 2003-2013

	GA, constant γ	GA, varying γ	Olley-Pakes	Greene, RE	DEA
L.TFP growth	-0.255** (0.121)	-0.229 (0.144)	-0.428** (0.175)	-0.277*** (0.099)	-0.290** (0.135)
L.TFP GAP	0.134 (0.135)	0.533 (0.318)	-0.092 (0.173)	0.447* (0.221)	0.379 (0.415)
L.log R&D	-0.032 (0.145)	0.195 (0.151)	-0.051 (0.078)	0.087 (0.078)	0.018 (0.035)
LD.HC	0.483 (0.358)	0.993 (0.587)	0.587 (0.375)	0.387 (0.542)	0.560 (0.576)
L.R&D*GAP	0.031 (0.068)	-0.151 (0.112)	0.076 (0.080)	-0.070 (0.076)	-0.040 (0.129)
LD.HC*GAP	0.023 (0.079)	-0.085 (0.074)	-0.052 (0.075)	-0.076** (0.037)	-0.130** (0.061)
2008-2010	-0.057** (0.024)	-0.082*** (0.016)	-0.037 (0.022)	-0.076*** (0.025)	-0.089*** (0.020)
2011-2013	-0.005 (0.025)	-0.064** (0.026)	0.067*** (0.022)	-0.006 (0.019)	-0.026* (0.013)
D.spillover	-0.002 (0.027)	0.020 (0.029)	0.076** (0.034)	0.059*** (0.018)	0.017 (0.013)
GAP2003	-0.107 (0.086)	-0.017 (0.071)	-0.076 (0.082)	-0.096 (0.116)	-0.079 (0.090)
Intercept	-0.052 (0.444)	-0.654 (0.447)	0.081 (0.190)	-0.319 (0.283)	-0.101 (0.088)
AR_OLS	-0.154	-0.203	-0.336	-0.261	-0.194
AR_FE	-0.243	-0.208	-0.359	-0.392	-0.281
Hansen	22.235	21.923	22.603	22.361	17.897
p-Hansen	0.725	0.465	0.706	0.719	0.712
AR1	-3.073	-2.813	-2.564	-3.146	-3.137
p-AR1	0.002	0.005	0.010	0.002	0.002
AR2	0.442	0.617	0.449	0.694	1.245
p-AR2	0.658	0.537	0.653	0.488	0.213
F	15.383	5.156	6.950	16.209	7.556
p-F	0.000	0.001	0.000	0.000	0.000

J	38	33	38	38	33
N	214	214	214	208	187
N-region	24	24	24	24	21
N-country	13	13	13	13	12

Source: Authors' calculations on Eurostat data.

Note: Dependent variable is TFP growth. Windmeijer finite sample corrected standard errors.

AR_OLS denotes the autoregressive term from the pooled OLS and AR_FE denotes the autoregressive term from the fixed effects panel estimator.

γ denotes the labour share in total output and is set constant and equal to 0.67 in the "GA, constant γ model" and is varying in time and across countries in the "GA, varying γ model".

***, **, * stand for 1%, 5% and 10% level statistical significance respectively

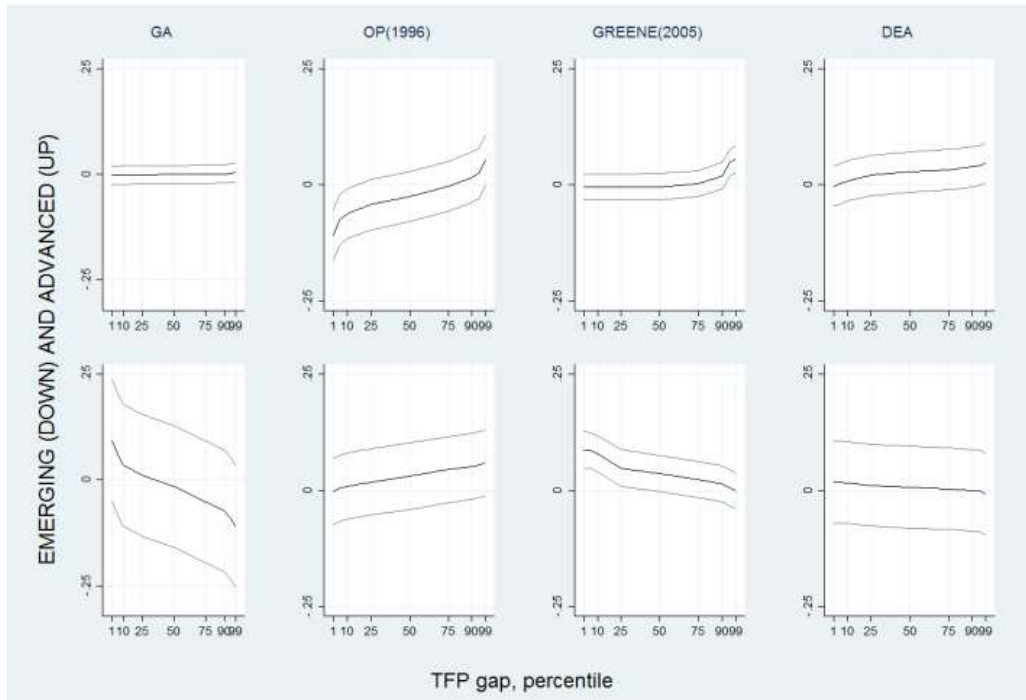


Figure B1. R&D, marginal effect on TFP growth (%) with 90% confidence intervals

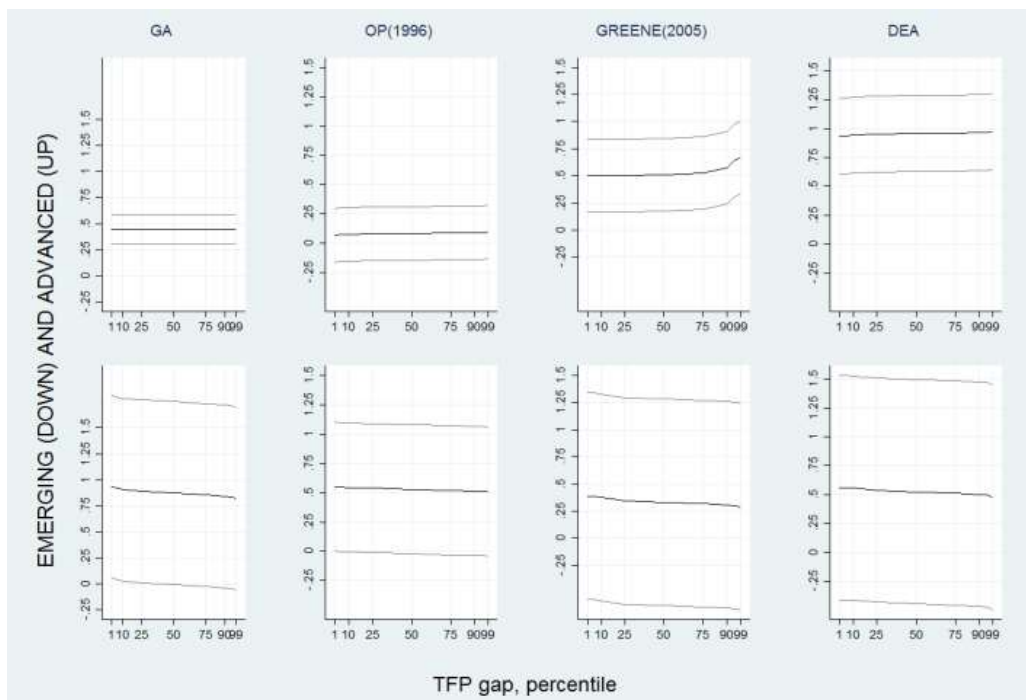


Figure B2. Human Capital, marginal effect on TFP growth (%) with 90% confidence intervals

Appendix C: Summary descriptive statistics on the estimation sample

Table C1. Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Real R&D expenditures per capita, EUR	203.217	195.321	1.718	1104.154	766
Logarithm human capital first component	3.124	0.422	1.895	3.915	766
Logarithm human capital first component, alternative	3.149	0.411	1.951	3.935	752
Growth Accounting, constant labour share	Mean	Std. Dev.	Min.	Max.	N
Annual TFP growth, %	1.8	6.1	-39.4	27.0	766
Logarithm TFP gap	1.013	0.649	0	2.966	766
Logarithm TFP gap 2003	1.008	0.77	0	2.951	766
Logarithm regional TFP spillover	2.936	0.953	0.389	5.68	766
Growth Accounting, varying labour share	Mean	Std. Dev.	Min.	Max.	N
Annual TFP growth, %	0.8	5.9	-39.6	20.5	766
Logarithm TFP gap	0.98	0.562	0	2.705	766
Logarithm TFP gap 2003	0.929	0.63	0	2.651	766
Logarithm regional TFP spillover	2.626	0.924	0.28	5.394	766
Olley-Pakes, 1996	Mean	Std. Dev.	Min.	Max.	N
Annual TFP growth, %	0.5	6.2	-27.5	30.9	766
Logarithm TFP gap	0.996	0.253	0	1.69	766
Logarithm TFP gap 2003	1.012	0.261	0	1.62	766
Logarithm regional TFP spillover	2.145	1.024	0.095	4.971	766
Greene (2005) random effects model	Mean	Std. Dev.	Min.	Max.	N
Annual TFP growth, %	0.21	6.57	-32.91	23.28	742
Logarithm TFP gap	0.291	0.358	0	1.257	742
Logarithm TFP gap 2003	0.323	0.421	0	1.27	742
Logarithm regional TFP spillover	4.606	0.947	1.815	6.865	742
Data Envelopment Analysis	Mean	Std. Dev.	Min.	Max.	N
Annual TFP growth, %	-0.5	6.3	-34.2	19.8	618
Logarithm TFP gap	0.332	0.16	0	0.698	618
Logarithm TFP gap 2003	0.351	0.173	0	0.718	618
Logarithm regional TFP spillover	4.283	0.941	1.946	6.486	618

Appendix D: NUTS-1 level regions by countries

Table D1. NUTS-1 level regions by countries

COUNTRY (Regions)	NUTS CODES AND REGION NAMES
Austria (3)	AT1: Ostösterreich; AT2: Südösterreich; AT3: Westösterreich
Belgium (3)	BE1: Région de Bruxelles-capital/Brussels Hoofdstedelijk Gewest; BE2: Vlaams Gewest; BE3: Région Wallonne
Bulgaria (2)	BG3: Severna i Yugoiztochna Bulgaria; BG4: Yugozapadna i yuzhna tsentralna Bulgaria
Croatia (1)	HR0: Hrvatska
Cyprus (1)	CY0: Kypros
Czech Republic (1)	CZ0: Česká Republika
Denmark (1)	DK0: Danmark
Estonia (1)	EE0: Eesti
Finland (2)	FI1: Manner-Suomi; FI2: Åland
France (9)	FR1: Île De France; FR2: Bassin Parisien; FR3: Nord-Pas-De-Calais; FR4: Est; FR5: Ouest; FR6: Sud-Ouest; FR7: Centre-Est; FR8: Méditerranée; FR9: Départements D'outre-Mer
Germany (16)	DE1: Baden-Württemberg; DE2: Bayern; D3: Berlin; D4: Brandenburg; DE5: Bremen; DE6: Hamburg; DE7: Hessen; DE8: Mecklenburg-Vorpommern; DE9: Niedersachsen; DEA: Nordrhein-Westfalen; DEB: Rheinland-Pfalz; DEC: Saarland; DED: Sachsen; DEE: Sachsen-Anhalt; DEF: Schleswig-Holstein; DEG: Thüringen
Greece (4)	EL1: Voreia Ellada; EL2: Kentriki Ellada; EL3: Attiki; EL4: Nista Aigaiou, Kriti
Hungary (3)	HU1: Közép-Magyarország; HU2: Dunántúl; HU3: Alföld és Észak
Ireland (1)	IE0: Ireland
Italy (5)	ITC: Nord-Ovest; ITF: Sud; ITG: Isole; ITH: Nord-Est; ITI: Centro (IT)
Latvia (1)	LV0: Latvija
Lithuania (1)	LT0: Lietuva
Luxemburg (1)	LU0: Luxembourg
Malta (1)	MT0: Malta
Netherlands (4)	NL1: Noord-Nederland; NL2: Oost-Nederland; NL3: West-Nederland; NL4: Zuid Nederland
Poland (6)	PL1: Region Centralny; PL2: Region Poludniowy; PL3: Region Wschodni; PL4: Region Polnocno-Zachodni; PL5: Region Poludniowo-Zachodni; PL6: Region Północny
Portugal (3)	PT1: Continente; PT2: Região Autónoma Dos Açores; PT3: Região Autónoma da Madeira
Romania (4)	RO1: Macroregiunea Unu; RO2: Macroregiunea Doi; RO3: Macroregiunea Trei; RO4: Macroregiunea Patru
Slovakia (1)	SK0: Slovensko
Slovenia (1)	SI0: Slovenija
Spain (7)	ES1: Noroeste; ES2: Noreste; ES3: Comunidad De Madrid; ES4: Centro (ES); ES5: Este; ES6: Sur; ES7: Canarias
Sweden (3)	SE1: Östra Sverige; SE2: Södra Sverige; SE3: Norra Sverige
United Kingdom (12)	UKC: North East (England); UKD: North West (England); UKE: Yorkshire and the Humber; UKF: East Midlands (England); UKG: West Midlands (England); UKH: East of England; UKI: London; UKJ: South East (England); UKK: South West (England); UKL: Wales; UKM: Scotland; UKN: Northern Ireland

Source: Eurostat RAMON – Reference and Management of Nomenclatures,

<http://ec.europa.eu/eurostat/ramon/nomenclatures>