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# Technological convergence across European regions

**JEL Classification:** *R12; C23; O33; O47*

**Keywords:** *technological convergence; TFP; EU regions*

**Abstract**

**Research background:** Given the pivotal role of innovations and technological progress in shaping the economic development of regions and the crucial significance of spatial dimension of innovation processes at the regional level, the assessment of technological convergence in the regional scope becomes an essential research problem. Technological convergence could be identified on the basis of the analysis of total factor productivity (TFP). The significance of the technological convergence analysis results from the fact that income convergence can be both accelerated or impeded, depending on whether the initial differences in the level of technology (TFP) decrease or increase over time.
**Purpose of the article:** The aim of the paper is twofold. Firstly, we attempt to develop a theoretical framework for the analysis of the technological convergence. Secondly, we investigate the technological convergence (on the basis of the TFP analysis) across European regions.
**Methods:** During the first stage of the research, we employ the multiplicatively-complete Färe-Primont index to calculate TFP. The second stage of the study includes estimation of spatial panel models applied to assess the level of technological convergence across European regions. The research sample consists of 273 NUTS 2 European Union (EU) regions over the period 2010–2016.
**Findings & Value added:** The results of the study confirm a clear division of Europe into the Western European regions with high TFP values and the Eastern European regions with low TFP level. The research also shows that in the Eastern European regions the process of reducing the differences in the productivity levels is faster than in Western European regions. Since the issue of technological convergence is still not sufficiently explored in the relevant literature our paper

attempts to fill a cognitive and methodological gap in the investigation of the technological convergence in the European regional space.

## Introduction

Abundant evidence in the relevant literature indicates that the existing disparities in regional economic development can be predominantly attributed to differences in productivity (Islam, 2003a). A significant part of the identified differences in the per capita income that remains unexplained after taking into account the differences in physical or human capital, can be attributed to Total Factor Productivity (TFP) that determines how efficiently and intensely the available inputs are used in production. Recent theories of growth and development suggest that heterogeneity with respect to technological conditions in general and TFP in particular are identified as the most decisive factors responsible for the absence of absolute income convergence of countries and/or regions. This view is consistent with Otsuka *et al.* (2010), who showed that the majority of regional economic growth is explained by a region's unique technological potential. In this light, the analysis of technological convergence in the regional scope, which is the process of making the regions similar to each other in terms of the level of technology, becomes an essential research problem. Since the issue of technological convergence is still not sufficiently explored in the relevant literature our paper attempts to fill a cognitive and methodological gap in the investigation of the technological convergence in the European regional space.

Bearing in mind the aforementioned considerations, the aim of the paper is twofold. Firstly, we attempt to develop a theoretical framework for the analysis of the technological convergence. Secondly, we investigate the technological convergence (on the basis of the TFP analysis) across European regions.

In the first stage of the research, we employ the multiplicatively-complete Färe-Primont index to calculate TFP as this index is considered to be better applicable in wider economic context in comparison to the Malmquist TFP index (O'Donnell, 2012). The second stage of the study includes estimation of spatial panel models which are applied to assess the level of technological convergence across 273 EU regions at the NUTS 2 level.

The reminder of the paper is organized as follows. In the next section, a brief overview of the literature illustrating the concept of technological convergence, its features and measurement is presented. The third section describes the data and methods adopted to calculate TFP and technological convergence across EU regions. The next two sections present, respectively, the results of the analysis along with a brief discussion of the main findings. The final section summarizes the results and discusses their policy implications.

## Literature review

The empirical literature on convergence is large and rapidly expanding (Abreu *et al*., 2005). For over 30 years, intensive research on the convergence processes resulted in identification of different kinds of convergence, as well as emergence of various approaches to its assessment (Islam, 2003b). Even though the complexity of this issue has not allowed so far to formulate its single, universal definition, it seems evident that the term 'convergence' most frequently refers to the process of diminishing the differences initially existing between individual objects, often regarding diverse phenomena, which can ultimately lead to a complete disappearance of those differences. Amongst many approaches employed in the relevant literature to identify the existence of convergence in the economic sense, the following two appear to be most commonly adopted: the beta convergence test (conditional and unconditional) and the sigma convergence test (Sala-i-Martin, 1990). The former approach involves investigation of the linear relationship between the average change in a given variable and its initial level over a given period of time. A negative association indicates that regions exhibiting lower initial levels of a given variable are able to realise a higher rate of its increase, thus leading to "catching up" with more developed regions. In turn the sigma convergence relies on the analysis of trends in the changes of the level of dispersion in a given variable between various regions. Under this approach, lower dispersion indicates that the analysed regions are converging.

Classical convergence refers to the Solow-Swan model of economic growth with its central hypothesis that diminishing returns to investment cause the growth rate of a given country to decline as it approaches its steady state level of per capita unit of effective labour, which implies, *ceteris paribus*, slower growth of richer economies than the poorer ones (Dowrick & Rogers, 2002). As Bernard and Jones (1996) point out, however, this approach ignores the role of technology and the potential for technology transfer and so, they suggest inclusion of technology transfer into the analysis that should provide a richer framework for convergence explanation. The assumption that technology levels and growth rates vary across countries allows to state that poor economies, characterised with a large technology gap, may face faster growth providing their ability to absorb technology (Fagerberg, 1994). Incorporation of technology transfer is visible in endogenous growth models where growth rates depend on the dynamics of technological catch-up (Howitt, 2000).

Initially, empirical studies set out to investigate the convergence process focusing on income differentials (both classical convergence and technological catch-up models contain the log of initial GDP per capita in the empirical estimating equations (Dowrick & Rogers, 2002)). However, the productivity dynamics analysis appears to be gaining an increasing importance in explaining economic inequalities across countries and regions (Easterly & Levine, 2001). As the regional development becomes increasingly dependent of the efficiency of innovation processes and technological progress (Crescenzi & Rodríguez-Pose, 2011), the attention of researchers has gradually shifted towards the technological aspects of convergence (Ramajo *et al.*, 2008; Ezcurra *et al.*, 2009; Di Liberto & Usai, 2013). The regional level of analysis seems to be relevant as regional disparities within the EU member states appear to persist or even to grow (Giannetti, 2002, Cappelen *et al.* 2003; Le Gallo & Dall'erba, 2008; Geppert & Stephan, 2008). Moreover, it is widely accepted that spatial effects have an impact on the process of regional growth as contiguous regions tend to grow at similar rates (Paci & Pigliaru, 2002; Fingleton, 2003).

Technological convergence can be defined as the process of making the regions similar to each other in terms of the level of technology. Most often, technological convergence is identified on the basis of TFP. This indicator is used to measure the joint effectiveness of all inputs combined in the production process. Changes in TFP, which are separate from changes in inputs, represent the joint effects of all input-augmenting technological improvements and the effect of Hicks-neutral technological change. The significance of the concept of technological convergence results from the fact that income convergence can be both accelerated and impeded, depending on whether the initial differences in the level of technology (TFP) decrease or increase over time (Islam, 2003b). Confirmation of this argument can be found in empirical studies as Maffezzoli (2006) demonstrated that the process of the convergence in relative TFP is the main determinant of the change in the shape of regional economic growth.

A wide range of different approaches is currently used in the literature to determine TFP. According to Schatzer *et al.* (2019), the choice of a model has an essential impact on estimation results for both TFP levels and TFP growth rates. Having reviewed most of the available methodologies for productivity estimation Del Gatto *et al.* (2011) suggest distinguishing between deterministic methodologies, whose output is a ‘calculated’ measure of TFP, and econometric ones, which yield ‘estimated’ productivity levels and/or growth rates as well as between frontier and non-frontier approaches.

The classical TFP approach stems from the Solow (1957) macroeconomic model based on the aggregate production function relating the total output of a given economy to the inputs of basic factors of production (i.e. capital and labour) and an exogenous variable describing the available technology. Provided that each economic agent operates efficiently, economic growth can be decomposed into contributions due to factor (capital and labour) accumulation and TFP growth, which is identified with technological progress. Under this approach, TFP is calculated residually and it is often referred as the “Solow residual” (Salinas-Jimenez *et al.*, 2006). However, when inefficiency occurs, the estimation of technical progress will be biased.

More recent studies, however, often adopt the frontier approach, which allows for the presence of inefficiencies resulting from the sub-optimal decisions of economic agents that prevent the actual output of a given economy from reaching its theoretically possible maximum demarcated by the frontier (Şeker & Saliola, 2018). It is focused on the decomposition of TFP growth into efficiency change, represented by movements of the economy towards or away from the production frontier, and technological progress represented by shifts of the production frontier (O’Donnell, 2012). This framework is based on the assessment of individual contributions of technological progress, changes in efficiency, and capital accumulation to the labour productivity growth. TFP is decomposed by means of productivity indices of which the most frequently employed in the empirical analyses is the Malmquist index. However, in the present paper, we employ Färe-Primont index in order to decompose TFP, as, according to O’Donnell (2012), this index is considered to be better applicable in wider economic context in comparison to the Malmquist TFP index that cannot always be interpreted as a measure of productivity change.

As it is commonly considered, the level of TFP growth for an economy lagging behind the technological frontier depends on innovation and technology transfer from the leader to the follower countries (Cameron *et al.*, 2005). Basing on the “neo-Schumpeterian” growth approach (Aghion & Howitt, 2006) TFP growth depends on the rate of innovation creation and on the rate of adoption or diffusion of new technologies in the regional economies. As Cameron *et al.* (2005) demonstrate a positive effect of distance from the technological frontier on the rates of productivity growth is observed. Other things equal, the further distance of an economy from the technological frontier, the higher its rate of TFP growth.

## Research methodology

On the basis of literature review, the following research hypothesis is formulated:

H1: *Technological convergence process occurs across the EU regions.*

The examined sample consists of 273 European Union (EU) regions at NUTS 2 level. Due to the lack of comparable data, we exclude the regions from Cyprus, Croatia and Ireland. At the initial stage of our study, we calculate the total factor productivity (TFP). TFP is defined as the ratio of aggregate output to aggregate input. We use one output and two input variables to estimate TFP. We use gross domestic product (GDP) at current market prices as the output variable. The input variables are employment (EMP) in thousand hours worked and gross fixed capital formation (GFCF). The latter consists of resident producers' investments, deducting disposals, in fixed assets during a given period. All input and output quantitative variables are scaled to have unit means, to solve the problems with their different orders of magnitude. The regional data on these variables have been extracted from the Eurostat database and covers the years 2010-2016. The data have a panel structure with 273 units and 7 periods.

We apply the Färe-Primont index to estimate the total factor productivity. It contains aggregator functions of the following form (O'Donnell, 2011):

$$Q(q) = D_O(x_0, q, t_0) \quad (1)$$

$$X(x) = D_I(x, q_0, t_0) \quad (2)$$

where $x_0$ and $q_0$ are vectors of representative input and output quantities, $t_0$ denotes a representative time period, and $D_0(.)$ and $D_I(.)$ are output and input distance functions.

The index is calculated as follows (O'Donnell, 2011):

$$TFP_{hs,it} = \frac{D_O(x_0,q_{it},t_0)}{D_O(x_0,q_{hs},t_0)} \times \frac{D_I(x_{hs},q_0,t_0)}{D_I(x_{it},q_0,t_0)} \quad (3)$$

It measures TFP of region $i$ in period $t$ relative to TFP of region $h$ in period $s$.

We employ DPIN program for the Färe-Primont index calculation. The program estimates the production technology and associated measures of productivity and efficiency using data envelopment analysis (DEA) linear programs (LPs). DEA is based on the assumption that the output and input distance functions representing the technology available in period *t* take the form:

$$D_O(x_{it}, q_{it}, t) = (q'_{it}\alpha)/(\gamma + x'_{it}\beta) \tag{4}$$

$$D_I(x_{it}, q_{it}, t) = (x'_{it}\eta)/(q'_{it}\phi - \delta) \tag{5}$$

DPIN computes Färe-Primont indexes by finding the solution of the following two LPs (O'Donnell, 2011):

$$D_O(x_0, q_0, t_0)^{-1} = \min_{\alpha,\gamma,\beta}\{\gamma + x'_0\beta: \gamma\iota + X'\beta \geq Q'\alpha; q'_0\alpha = 1; \alpha \geq 0\,; \beta \geq 0\} \tag{6}$$

$$D_I(x_0, q_0, t_0)^{-1} = \max_{\phi,\delta,\eta}\{q'_0\phi - \delta: Q'\phi \leq \delta\iota + X'\eta; x'_0\eta = 1; \phi \geq 0\,; \eta \geq 0\} \tag{7}$$

After calculating TFP values for NUTS 2 regions, the next step involves performance of convergence analysis. We apply the concept of β-convergence. Initial works in this area (Mankiw *et al.*, 1992; Barro & Sala-i-Martin, 1995) use the cross-sectional data models of convergence, while the later ones (Islam, 1995) employ models for panel data. Another important factor that should be taken into account in the analysis of regional convergence is the spatial dependence between regions. As spatial analysis techniques mature, scholars have focused on the influence of spatial dependence on regional efficiency instead of mere adoption of absolute or conditional convergence equation of economics (Ze-Lei *et al.*, 2017). Thus, we apply a spatial panel model to make an empirical analysis of EU regional productivity convergence.

The classical model of β-convergence for cross-section data is constructed as:

$$\ln\left(\frac{y_{iT}}{y_{i1}}\right) = \alpha + \beta\ln(y_{i1}) + \varepsilon_i \tag{8}$$

where $y_{i1}$ and $y_{iT}$ are the level of variable in the unit *i* in the first and the last period, respectively. The estimate of parameter β informs about the direction and intensity of the convergence process. If β is less than zero, it means that an absolute convergence occurs. By contrast, β greater than zero indicates divergence.

The use of the model for cross-section data causes that some information about the variability of spatial units' features between first and last period is lost. For this reason, the model for panel data should be applied, according to the following formula:

$$\ln\left(\frac{y_{it}}{y_{i,t-1}}\right) = \alpha + \beta\ln(y_{i,t-1}) + \eta_i + \gamma_t + \varepsilon_{it} \tag{9}$$

The panel data model contains both the individual and time effects which can be treated as fixed (FE) or random (RE).

The analysis of convergence for spatial units requires taking into account the spatial dependence between regions. The most comprehensive specification of spatial panel model for convergence study additionally includes spatially lagged dependent and independent variables, and spatially lagged error, given by:

$$\begin{gathered}\ln\left(\frac{y_{it}}{y_{i,t-1}}\right) = \alpha + \beta_1\ln(y_{i,t-1}) + \beta_2 W\ln(y_{i,t-1}) + \rho W\ln\left(\frac{y_{it}}{y_{i,t-1}}\right) + \\ \eta_i + \gamma_t + u_{it}, \quad u_{it} = \lambda W u_{it} + \varepsilon_{it}\end{gathered} \tag{10}$$

The parameters $\beta_2$ and $\rho$ indicate the effects of productivity and its changes in the regions on the productivity changes in neighbouring regions. If $\lambda = 0$, the model (10) is the SAR (spatial autoregressive) convergence model, and if $\rho = 0$, it is the SEM (spatial error model) convergence model.

In order to examine the differences in the convergence processes between the 'old' EU member states and the 'new' ones (after the 2004 enlargement), the additional component is included in the model. In result, the final version of the model becomes as follows:

$$\begin{gathered}\ln\left(\frac{y_{it}}{y_{i,t-1}}\right) = \\ \alpha + \beta_1\ln(y_{i,t-1}) + \beta_2 N ln(y_{i,t-1}) + \beta_3 W\ln(y_{i,t-1}) + \\ \rho_1 W\ln\left(\frac{y_{it}}{y_{i,t-1}}\right) + \eta_i + \gamma_t + u_{it}, \quad u_{it} = \lambda W u_{it} + \varepsilon_{it}\end{gathered} \tag{11}$$

where $N$ is a dummy variable which takes the value of 1 if the region is in the country of the 'new' EU, and 0 otherwise.

In our study, we use the spatial weights matrix which reflects the intensity of the geographic and economic relationship between regions. They are based on the distances between regions and the level of GDP per capita. The spatial weights are calculated as follow:

$$w_{ij} = \begin{cases} \frac{q_{ij}}{d_{ij}}, & i \neq j \\ 0, & i = j \end{cases}, \tag{12}$$

where $q_{ij}$ is the absolute value of the difference in the average level of GDP per capita between regions $i$ and $j$, $d_{ij}$ is the distance between the centroids of regions $i$ and $j$. The matrix is row standardized.

## Results

During the first stage of the study we calculate TFP using the Färe-Primont index. The input variables are employment and gross fixed capital formation, and the output variable is GDP. Figure 1 present the average levels of TFP in 273 NUTS regions in years 2010–2016. The regions with the highest average level of TFP values are located in the United Kingdom. Eight of the top ten regions (fifteen of the top twenty regions) are located in this country. As expected, first and third positions occupy Inner London — West and Inner London — East. Surprisingly, high positions in the ranking are occupied by the Greek regions. Attica takes the second place, and Notio Ejeo — nineteenth place in the ranking. The other countries with regions exhibiting high levels of TFP values are two small countries — Cyprus and Luxembourg, and Denmark, Portugal, the Netherlands (Groningen — fifth position), Italy and Germany (Düsseldorf — thirteen position, Arnsberg — twentieth position). The regions with the highest TFP values belong to the ‘old’ EU, which specializes in knowledge-intensive services (KIS) (Marrocu *et al.*, 2013).

At the bottom of the ranking there are regions with the lowest TFP levels. All of them, except one, are located in the countries of Central and Eastern Europe. This exception is a British region — North Eastern Scotland (sixth lowest position). The regions with the lowest average level of TFP values are located in Bulgaria (Yuzhen Tsentralen — second position, Yugoiztochen — third position, Severoiztochen — fourth position) and Romania (Bucuresti-Ilfov — first position, Nord-Est — fifth position). The other countries with regions revealing low levels of TFP values are Czech Republic (Severozápad — eleventh position, Strední Cechy — thirteen position), Estonia, Hungary (Dél-Dunántúl — seventh position), Latvia and Poland (Podlaskie — eighth position, Warminsko-Mazurskie — twelfth position). In contrast to the previous group of regions, the regions with the lowest levels of TFP belong to the ‘new’ Europe, which specializes in low-tech manufacturing (LTM) (Marrocu *et al.*, 2013).

At the second stage of the study, we use spatial panel model to verify convergence process of TFP between NUTS 2 regions. The comprehensive model (11) with spatial weights (12) in two versions (fixed and random effects) is applied. We use the QML estimator derived by Lee and Yu (2010a) to estimate the parameters of the model with fixed effects and the ML estimator derived by Lee and Yu (2010b) for the model with random effects. Time effects turn out to be not significant (p-value near 1) and thus they are removed from the model. Table 1 presents the estimation results.

As the study is conducted for a group of regions that covers a certain population (NUTS regions), the FE model is preferred over the RE model. We also perform the Hausman test to differentiate between the FE model and the RE model. The results of the test provide a strong evidence in favour of the FE model (chi2 = 647,55, p = 0). The Wald test shows high significance of spatial terms in the models, which confirms the validity of including spatial dependencies in the analysis.

The results show that productivity in European regions clearly converges. It means that in 2010–2016 productivity in NUTS2 regions with low levels of TFP grew faster than in regions with high levels of TFP. In consequence, the productivity of European economies was getting closer, which proves positive tendencies and effectiveness of the innovation policy tools used by the institutions of the European Union. We also verify the difference in intensity of convergence process between the regions of 'old' and 'new' EU member states. The outcomes for the FE model indicate a little stronger convergence for regions in the 'old' EU, but the difference is statistically insignificant ($p > 0.1$). It means that both 'old' and 'new' EU countries follow the similar path of convergence process.

The analysis of spatial effects gives ground to a statement that the level and changes of productivity in a given region have impact on changes in productivity levels in other regions. The higher the level of TFP and the higher its growth in the neighbouring regions are, the higher growth of TFP in a region is. This may be explained by a motivating effect of innovation performance in EU regions on innovation performance in other regions. This stimulation is beneficial for the entire European Union because it strengthens its position in relation to other world economies, especially China and USA.

## Discussion

The results of our research allow to identify the technological convergence process across the EU NUTS2 regions over the years 2010–2016. We hypothesise and demonstrate that productivity in regions with low levels of TFP grew faster than in those with high levels of TFP. These findings are in line with Männasoo *et al.* (2016) who examined regional productivity convergence for 99 European NUTS 1 regions in 2000–2013 and demonstrated that the fastest growth of TFP occurred in the catching-up regions of CEE.

Our findings seem particularly interesting in comparison to the results of a study by Di Liberto and Usai (2013) who analysed 199 NUTS 2 regions in EU15 (plus Norway and Switzerland) between 1985 and 2006, but did not find the evidence of TFP convergence, arguing that TFP dispersion in the 'old' member countries was virtually constant. In this light, the TFP convergence across the regions of the enlarged EU that we observed in our study results from external productivity spillovers in the regions of the 'new' member states arising from apparent productivity gap, as suggested by Männasoo *et al.* (2016).

The productivity convergence across the EU regions is likely driven by implementation of European policy goals aiming at diminishing development disparities. Our results might also be viewed as an evidence of the effectiveness of the Europe 2020 Strategy (European Commission, 2010) which promotes innovation and knowledge transfer across EU that foster economic factor productivity cohesion.

The presented evidence of faster growth of productivity in the 'new' member states is also in line with the findings of Balcerzak (2015), who demonstrated a significant progress made by these countries in implementation of Europe 2020 Strategy, which allowed to reduce the gap to 'old' member states (EU 15) roughly by half between 2004–2013.

The statistically insignificant differences in the TFP convergence intensity between the regions of 'old' and 'new' member states have led us to conclusion that both these groups of regions follow a similar path of technological convergence process. In the light of contemporary economic growth models, particularly those stemming from the Solow growth model, these similar patterns of technological convergence are likely resulting in the analogous developments in GDP convergence, as observed, for instance, by Kisiała and Suszyńska (2017).

Even though the TFP convergence process leads to narrowing the overall productivity gap across the examined European regions our results also reveal that there are still considerable disparities in this scope. In line with the results of previous studies (among others: Beugelsdijk *et al.*, 2018, Männasoo *et al.*, 2016, Di Liberto & Usai, 2013) our findings indicate the presence of relatively high and largely persistent heterogeneity in TFP levels across EU regions, especially pronounced between the 'old' and 'new' member states. The above conditions likely reflect the differences in the overall innovation capacities of particular regions. We argue that the regions of ‘old’ member states are more capable of creating new knowledge and technologies and thus are able to sustain already high TFP productivity, whereas the vast majority of ‘new’ member states rely on imitation and absorption of technologies developed elsewhere (see eg. Marrocu *et al.*, 2013).

Combining the findings of TFP convergence with the persistence of the overall disparities in productivity levels across the EU regions seems to be consistent with the results of Soszyńska (2012) who argues that the technological convergence in the EU27 countries reflected mostly the effects of imitation rather than innovation.

As suggested by Aghion and Howitt (2006), decreasing productivity gap requires attracting investors from technologically advanced regions and therefore creating an investor-friendly macroeconomic and social conditions. An important role is also played by economic policies promoting openness enabling technology transfer between ‘new’ and ‘old’ European countries (Tica & Šikić, 2019; Pietrucha *et al.*, 2018). This model, however, could likely result in strengthening the bi-polar model of innovators and imitators. Breaking this technology-dependence pattern requires an efficient and consistent policy aimed at fostering creative innovation potential in less developed regions. Additionally, the revealed spatial dimension of TFP dispersion patterns suggests that a key focus of innovation policy in peripheral regions should be placed on development and fostering ICT as it might significantly decrease the difficulties in access to new technologies caused by the physical distance from frontier regions.

In this context, special significance should be assigned to the proper development of institutional framework supporting the smart development of less advanced regions, especially peripheral. As Balcerzak and Pietrzak (2016) point out, institutional reforms are crucial for fostering the reduction of productivity gap between ‘new’ and ‘old’ members of EU.

Implementation of policy might be, however, difficult in the less developed regions as they face significant structural obstacles in diminishing the productivity gap (see eg. Haider *et al.*, 2020, Bednář & Halásková, 2018).

In this context, an important contribution of our study arises from the evidence demonstrating the presence of significant spatial effects in TFP distribution. In particular, we find that the level and growth rate of TFP in a given region largely depend on the analogous conditions in the neighbouring regions. In this aspect, our results also adhere to the findings of previous studies that underline the significance of the spatial dimension for productivity growth (Männasoo *et al.*, 2018). Therefore, we argue that spatial dimension of developments of TFP across European regions strongly contributes to the disparities observed in this variable in the long-run.

## Conclusions

The results of conducted analysis support the main hypothesis of the study that technological convergence process occurs across the EU regions. Productivity grew faster in the regions with low initial levels of TFP than in the regions with high initial levels of TFP. A slight difference in the intensity of TFP convergence in all EU regions or its lack of significance confirms that the convergence of productivity in UE is a stable and sustainable process.

Moreover, the spatial effects analysis revealed that the level and growth rate of TFP in a given region largely depend on the level and dynamics of TFP in the neighbouring regions, thus providing an evidence of the significance of spillover effects in shaping regional development trajectories.

Last decades of European regional policy show a significant increase in actions and investments to reinforce the convergence process. Although disparities in TFP across the EU regions are still prominent, the observed technological convergence process provides evidence of validity of regional and innovation policy actions.

The main limitation of our study is related to the limited availability of statistical data at the NUTS2 level, as the investigation of TFP convergence process across regions requires long time series.

Since the crucial determinant of the existing differences in regional economic development can be attributed to differences in productivity, the revealed convergence in productivity across European regions should translate into convergence in regional economic development in a long-run. In this light, our analysis could be further extended by assessing the impact of regional characteristics such as innovation creation and absorption capacity, institutional environment, human capital, R&D intensity, trade openness or spatial characteristics on the technological convergence process across European regions. Identification of the key factors contributing to reduction of productivity gaps seems crucial from the standpoint of the effectiveness of European regional development and innovation policy.

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## Annex

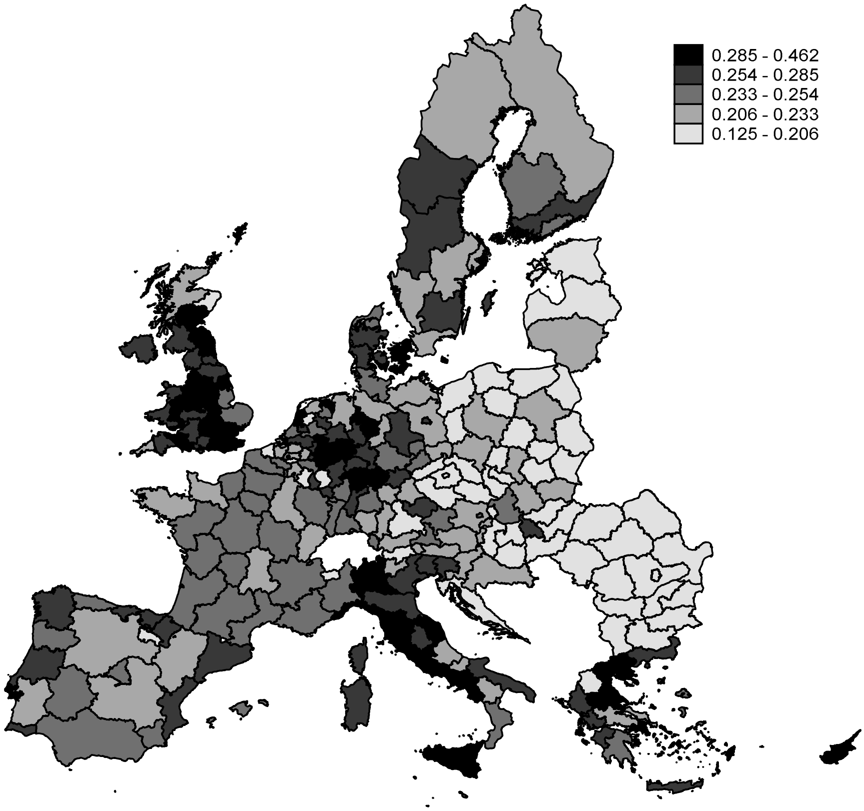
**Table 1.** Estimates of model parameters

| Parameters | Fixed effects | Random effects |
|---|---|---|
| $\alpha$ | | –0.019 |
| $\beta_1$ | –0.645*** | –0.163*** |
| $\beta_2$ | 0.024 | 0.027*** |
| $\beta_3$ | 0.653*** | 0.143*** |
| $\rho_1$ | 0.902*** | 0.867*** |
| $\lambda$ | –1.217*** | –1.153*** |
| direct effect (ln(TFP$_{i,t-1}$) | –0.637*** | –0.157*** |
| indirect effect (ln(TFP$_{i,t-1}$) | 0.767 | 0.049 |
| Log likelihood | 1610.0 | 1702.49 |
| Pseudo R2 | 0.077 | 0.097 |
| AIC | –3208.0 | –3388.98 |
| Wald test – spatial terms (p-value) | 579.88 (0.00) | 388.44 (0.00) |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: own calculations using STATA 15.

**Figure 1.** TFP in EU regions




Source: Map generated using STATA 15.