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Club Convergence in Productivity among European Regions: Recent Evidence and Policy Implications

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Abstract We use data on 155 NUTS regions, with the objective of i) generating TFP series over 1996-2018, and ii) testing for club-convergence. We also employ a logistic regression to identify the significant club-membership conditioning factors. We contribute to the literature on two main grounds. Firstly, we are the first to extract TFP series while applying a methodology that allows for heterogeneous production functions and accounts for cross-section dependence and nonstationarity. Secondly, we are the first to apply a TFP-club convergence analysis in the context of European regions over a large period of time that witnessed several shocks affecting the European integration. Our analysis reveals that: (i) most of the regions of the top TFP convergence clubs are located in the "old" EU-member states, with few regions situated in countries that joined the EU after 2004; (ii) several regions in the South are trailing with the risk of falling in a "productivity trap"; (iii) regions situated in new EU-member countries registered remarkable TFP growth rates; (iv) larger regional research and development resources, and higher employment in high-technology sectors are associated with a greater probability of being member of top-ranked TFP convergence clubs. Our findings suggest that the needs of the lagging regions should be prioritized in the agenda of the EU. In this respect, we suggest several recommendations.

Keywords: NUTS regions, regional TFP, club-convergence, Cohesion Policy

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I. Introduction

The European Union (EU) experienced expansions that brought together countries with varying levels of economic development and income. For instance, the average GDP per capita at constant 2015 prices for the core EU countries (also known as EU15) was 36,711 euros

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in 2004 and 39,764 euros in 2007. All countries that joined the EU in 2004 and 2007 had a lower GDP per capita.[1] In this respect, the EU strives to strengthen economic and social cohesion within the Union. Specifically, the European Commission carried out several policy measures, most notably the Cohesion Policy, to encourage investment, growth, and employment in the less developed regions of the EU[2]. However, the effectiveness and impact of the Cohesion Policy have been subjects of renewed discussion recently (Beugelsdijk et al., 2018; Kilroy and Ganau, 2020). This is because income discrepancies between the different regions persist (Crescenzi and Giua, 2020). Furthermore, the EU concluded that some regions are in, or at risk of falling into, a "development trap"[3]. The reason given is that innovation and the capital to innovate are concentrated in the western and north-western regions (European Commission 2022, 2023). The literature suggests that disparities in total factor productivity (TFP) are the main determinants of the rate of income convergence between countries (De la Fuente, 2002; Islam, 2003; Kijek et al., 2023). Moreover, income disparities that remain unexplained, after controlling for differences in labor and capital stocks, are mainly attributed to discrepancies in productivity (Kijek and Matras Bolibok, 2020).

In light of the preoccupying regional disparities across the EU, and in view of the importance of TFP to growth and economic convergence, we investigate in this paper regional productivity convergence in the EU and identify leading and lagging regions. To do so, we adopt a three-step approach. First, we generate regional TFP time series for the EU NUTS regions over the 1996-2018 period using the method proposed by Eberhardt and Teal (2020)[4]. Second, we employ the Phillips and Sul (2007) club convergence methodology (henceforth PS test) to test for

1) The GDP per capita at constant prices (2015, in euros) for countries that joined the EU in 2004 was: Slovenia (16,738), Malta (15,983), Cyprus (15,976), Czechia (12,713), Estonia (11,944), Slovakia (9,660), Hungary (9,724), Latvia (8,419), Lithuania (7,982), and Poland (7,451). While countries that joined the EU in 2007 had the following GDP per capita at constant prices (2015, in euros): Croatia (12,322), Romania (6,954), and Bulgaria (5,439). Variables are extracted from the OECD regional database.

2) The Cohesion Policy of the EU is a fundamental framework aimed at promoting and supporting the overall harmonious development of its member States and regions. Its primary goal is to reduce regional disparities in income, wealth, and opportunities, thereby fostering balanced economic, social, and territorial development across the EU.

3) In the context of the EU, a "development trap" refers to a situation where certain regions are unable to achieve sustainable economic growth and development despite efforts and investments. These regions face persistent structural challenges that prevent them from catching up with more developed areas.

4) NUTS or the "Nomenclature of territorial units for statistics" is a hierarchical system for dividing up the economic territory of the EU for statistical purposes. This system is used by Eurostat, the statistical office of the EU, to collect, develop, and harmonize regional statistics. It is also crucial for implementing the EU's regional policies and allocating funding, particularly through the Cohesion Policy. The NUTS classification is structured into three levels: NUTS 1, NUTS 2, and NUTS 3. The main difference between thee three levels is related to the functions of the classification and the number of inhabitants. NUTS 1 regions are the largest territorial units and the major socio-economic regions within a country, and constitute between 3 and 7 million inhabitants. NUTS 2 regions are the basic regions for the application of regional policies and constitute between 800,000 and 3 million inhabitants. NUTS 3 regions are the smallest units in the NUTS hierarchy and provide detailed local-level statistics and constitute between 150,000 and 800,000 inhabitants.

TFP-club convergence among European regions and identify the corresponding clubs. This method is particularly convenient for studying productivity convergence across the NUTS regions, in view of the large regional disparities highlighted above that render the existence of club convergence a plausible expectation. Third, we revert to a logistic regression to identify the critical conditioning factors of the TFP-club membership.

The contribution of this study can be summarized as follows. Firstly, we are the first to implement the method of Eberhardt and Teal (2020) to generate EU regional TFP series and test for convergence. This method has the advantage of allowing for heterogeneous production functions while accounting for cross-sectional dependence and non-stationarity. Secondly, while we are aware of one other study that tests for TFP-club convergence in EU regions (Kijek et al., 2023), our study differs from the latter on three key grounds. First, the period of analysis of that study extends over 11 years (2008-2018). Thus, the convergence test they apply is based on a short period, which might undermine their results. In this regard, our analysis covers a significantly larger period stretching 23 years (1996-2018). Second and unlike Kijek et al. (2023), our time horizon allows to explore the effects on the convergence dynamics of a number of major shocks that have impacted the EU-members, namely the 2004 enlargement of the Union, the 2007/8 financial crisis, and the euro-debt crisis. Moreover, our period covers fully or partially different programming periods of the European Regional Development Policy: 2000-2006, 2007-2013, and 2014-2020. Thus, to the best of our knowledge, our study is the first to investigate EU regional TFP convergence over a long period that covers these crucial milestones in EU history. Third, in addition to implementing the PS test and identifying the convergence clubs, we narrow down the analysis by focusing on the relative productivity performance (relative convergence paths) of a number of regions. This enables us to identify lagging regions and recommend targeted policy actions.

Our findings can be summarized as follows. First, we find support for club-convergence of regional TFP across NUTS regions. Second, the club cartography draws a number of demarcation lines. Indeed, most of the regions of the top-TFP clubs are part of "old" EU-member states, while few are located in new member states that joined the EU 2004 onwards. Moreover, the well-documented divide among old EU members between the "core" and the "periphery" seems still standing with many of the regions situated in northern and western Europe populating the top-TFP clubs, whereas most of the southern European regions are part of the low-productivity convergence clubs. Third, the case of Greek and several Italian regions is worrisome. Indeed, in addition to the fact that the latter regions fall in the lowest-TFP convergence clubs, their productivity convergence paths have been hit hard by the 2007/8 crisis and the 2011 euro-debt crisis, and are on a downward trajectory. In effect, those regions seem to be caught in a "productivity trap". This finding echoes the alarming concern raised by the EU about regions in southern Europe falling into a development trap (European Commission, 2022). Fourth, although the productivity of the new member states is still below the sample mean, they have registered remarkable growth rates over the period. This is especially the case of several regions in Poland that are embarking on a catch-up process. Lastly, our analysis suggests that two factors are associated with a greater likelihood of being a member of high-TFP clubs: research and development (R&D) and employment in knowledge intensive sectors.

The paper proceeds as follows. Section 2 provides an overview of the literature. Section 3 lays out the empirical strategy and the data used. Section 4 presents the findings of the club-convergence test as well as the results of the ordered logit model. Section 5 explores the productivity dynamics in a number of critical regions. Section 6 concludes.

II. Literature Review

The literature identifies four types of convergence (Kijek et al., 2023). The first one is the *beta* convergence introduced by Sala-i-Martin (1990). *Beta* convergence implies that economies with high-level of technology exhibit a lower rate of growth in technology compared to low-technology level economies. If all the economies converge to the same level of technology, *beta* convergence is said to be absolute. On the other hand, conditional convergence implies that economies with similar characteristics tend to converge towards a similar growth path but not necessarily toward a common level of technology. The second one, *sigma* convergence, assumes decreasing dispersion of technological progress across economies. Multiple papers explored these two types of convergence in the regional European context. Most studies using these approaches find evidence for absolute convergence (Escribá-Pérez and Murgui-García, 2019; Kijek et al., 2023) or conditional convergence (Marrocu et al., 2013; Männasoo et al., 2018; Escribá-Pérez and Murgui-García, 2019; Kijek and Matras Bolibok, 2020; Siller et al., 2021; Kijek et al., 2023)[5].

The third one is *stochastic* convergence introduced by Bernard and Durlauf (1995); it focuses on the long-run behavior of the differences in technology across economies. It examines whether productivity levels of different regions are tending towards a common steady state, despite short-term fluctuations. Empirically, in the presence of stochastic convergence, technological differences between economies should follow a stationary process. Most studies using this method find that, while weak convergence is evident, consistent differences across the European regions, and in some cases, within the same country persist (Kijek et al., 2023; Burda and Severgnini, 2018; Byrne et al., 2009; D'Uva and De Siano, 2011).

The last one is the *club* convergence hypothesis put forth by Fischer and Stirbock (2004).

5) Di Liberto and Usai (2013) is one of the few studies that don't find evidence for convergence in the regional European context.

This hypothesis posits that distinct groups—countries, states, sectors, or regions—within a "club" converge to a local steady-state equilibrium. It acknowledges the existence of distinct "clubs" within the regional/global economy, where economies with similar characteristics, may converge among themselves but not necessarily with the wider economy (Castellacci and Archibugi, 2008). Within this context, Phillips and Sul (2007, 2009) proposed a new methodology of panel club convergence testing that has several advantages over other tests such as the lack of the need for the assumption of stationarity of the variables, the presence of common factors across the panel, or the presence of cointegration between variables.

Largely driven by the significant disparities among NUTS regions, club convergence testing has gained popularity recently. A large body of the literature finds evidence of club-clustering in per capita income among NUTS regions (Bartkowska and Riedl, 2012; Simionescu, 2015; von Lyncker and Thoennessen, 2017; Cutrini, 2019). More recently, authors have examined club convergence among NUTS regions in areas relevant for productivity: Barrios et el. (2019) and Kijek et al. (2022) looked at convergence in, respectively, innovation activity and R&D expenditures. Only one paper, Kijek et al. (2023), investigates club convergence in TFP across European regions for the period 2008-2018. Results from these studies support the club convergence hypothesis, with regions in northern and western Europe being members of the top performing clubs and regions in eastern and southern Europe being part of the least performing ones.

III. Methodology, Sample and Data

First, we generate regional TFP series by estimating Cobb-Douglas production functions for 155 NUTS-regions over the period 1995-2018. Given that the estimation method is based upon a first-differencing process, the resulting TFP estimates span the 1996-2018 period. Second, we use the PS club convergence test to investigate productivity convergence among NUTS regions. Lastly, we estimate an ordered logit model to examine the key factors driving TFP club-membership.

A. TFP extraction

Deriving regional TFP levels from log-linearized Cobb-Douglas production functions is a standard practice (Marrocu et al., 2013; Männasoo et al., 2018; Siller et al., 2021). In doing so, authors have typically accounted for the possible endogeneity of the inputs, and spatial interconnections. In addition, employing a flexible modelling approach for TFP, accounting for an initial TFP level as well as its evolution over time (an evolution that is common to all units as well as idiosyncratic TFP progressions), is key to avoid misspecification. Further, using methods accommodating heterogeneous production functions is warranted in view of the regional disparities underlying the production process. Finally, attuning to the likely nonstationarity of the data is essential to preclude spurious results. In view of this, to extract regional TFP series, we apply the methodology proposed by Eberhardt and Teal (2020) that considers the aforementioned points. Their approach allows for parameter heterogeneity in the production function and accommodates cross-section dependence (including spatial connections). Further, they apply the augmented mean group (AMG) estimator that augments the production functions with proxies of the - possibly nonstationary - unobserved factors underlying TFP. Their method is summarized as follows.

For $i=1,\ldots,N$ region-country (for simplicity, we use "region" throughout the text) and $t=1,\ldots,T$ years, the following synthesizes the AMG-estimation procedure:

$$Stage\ 1: \Delta y_{it} = \beta^l \Delta l_{it} + \beta^k \Delta k_{it} + \sum\nolimits_{t=2}^{T} r_t \Delta D_t + u_{it} \ \ (1) \Rightarrow \hat{r}_t = \widehat{CDP}_t$$

$$Stage\ 2: y_{it} = \alpha_i + \beta_i^l l_{it} + \beta_i^k k_{it} + g_i t + d_i \widehat{CDP}_t + u_{it} \ \ (2) \Rightarrow \hat{\beta}^c_{AMG} = N^{-1} \sum_{i=1}^{N} \beta_i^c ; c = l, k$$

The first stage is an ordinary least squares estimation of the regional production function with the following variables (all expressed in first differences): GDP (y_{it}), labor (l_{it}), capital (k_{it}) (all in natural logs), a set of year dummies (D_t), and u_{it} (a white noise). Year dummies' estimates represent the time evolution of unobservable factors along sample regions (the so-called "common dynamic process" (CDP)). The CDP is interpreted as the progression of common TFP[6]. Stage 2 is a set of N region-specific regressions whereupon parameter estimates are averaged across regions[7]. The region-based production functions are extended to include region-specific linear trends (t) and the estimated CDP from the previous stage[8].

Figure 1 shows the evolution of the CDP over 1996-2018. The figure reveals a clear upward trend with an evident break in the aftermath of the 2007/08 international financial and economic crisis. The recovery started around 2009/10 and continued afterwards, with a slight slump in 2011-2013 reflecting the 2011 euro-debt crisis.

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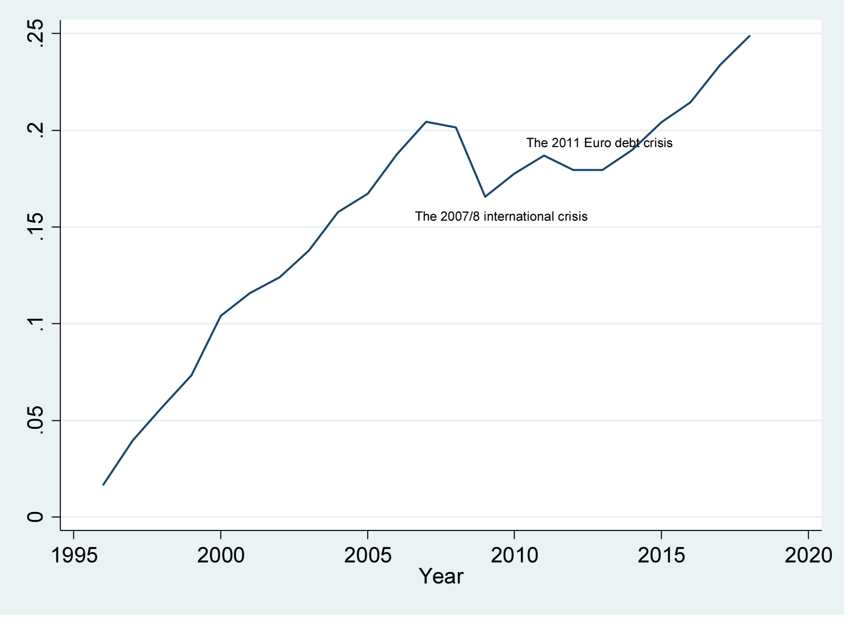
6) The CDP captures the mean progression of unobserved common factors. It incorporates shocks of universal nature impacting all sample units (e.g. the 2007/8 financial crisis).

7) Eberhardt and Bond (2009) showed that the AMG estimator yields unbiased estimates under various conditions and does not suffer from the typical issues related to the use of estimated regressors from a first-stage regression.

8) The linear trends are supposed to reflect omitted idiosyncratic factors affecting GDP (e.g. the quality of institutions).

Figure 1. Time evolution of the common dynamic process



Eberhardt and Teal (2020) demonstrated that in the presence of heterogeneous parameters, cross section unit-fixed effects can no longer be regarded as initial TFP levels. Instead, they suggest a method to extract unit-specific TFP levels that accommodates parameter heterogeneity. We adapt their methodology to the case of a production function with two inputs and present it in the following steps.

First, we calculate *adjusted* GDP:

$$y_{it}^{adjusted} = y_{it} - \hat{g}_i t - \hat{d}_i \widehat{CDP}_t \tag{3}$$

where y_{it} is GDP; estimated coefficients $(\hat{g}_i, \ \hat{d}_i)$ are obtained from region-specific AMG-estimation of equation (2); for any given year, t refers to its count value; and $\widehat{CDP}_t$ corresponds to the value of the common dynamic process at year t. $y_{it}^{adjusted}$ is therefore GDP deprived of the effect of unobservables over time.

Second, we regress $y_{it}^{adjusted}$ on inputs to derive region-specific coefficients $(\hat{a}_i, \hat{b}_i, \hat{c}_i)$:

$$y_{it}^{adjusted} = a_i + b_i l_{it} + c_i k_{it} + \epsilon_{it} \tag{4}$$

Third, we compute initial year TFP:

$$TFP_{i,\ initial\ year} = \hat{a}_i + \hat{b}_i l_{i,initial\ year} + \hat{c}_i k_{i,\ initial\ year} \tag{5}$$

Region-specific initial year TFP is thus obtained while considering parameter heterogeneity and initial year values of inputs.

Fourth, for years following the initial year, TFP is calculated as:

$$TFP_{i,t} = TFP_{i,\ initial\ year} + \hat{g}_i t + \hat{d}_i \widehat{CDP}_t \tag{6}$$

Equation (6) postulates that region-specific TFP at year *t* is the sum of initial year TFP and TFP evolution over time.

B. The PS convergence test

We use the PS convergence approach (known as *log-t* regression test) to test whether all the regions in our sample converge to a unique equilibrium. The null hypothesis of the test assumes convergence for all the regions while the alternative hypothesis assumes non-convergence for some regions. The alternative hypothesis does not imply strict divergence but club-convergence clustered around different steady-state levels. The absence of a unique equilibrium in favor of multiple equilibria is due to heterogeneity across regional economies. If such a uniform equilibrium does not exist, then it identifies endogenously sub-groups with similar transition paths (Du, 2017).

Here below, we briefly describe the methodology proposed by Phillips and Sul (2007). They decompose a panel date variable X_{it} into two components: one systematic, g_{it}, and one transitory, a_{it}:

$$X_{it} = g_{it} + a_{it} \tag{7}$$

They then separate the common, μ_t, and idiosyncratic, δ_{it}, components in X_{it} by transforming (7) as follows:

$$X_{it} = \left(\frac{g + a_{it}}{\mu_t}\right)\mu_t = \delta_{it}\mu_t \quad \text{for } all\ i,\ t$$

According to Phillips and Sul (2007), μ_t represents the aggregate common behavior of X_{it}, whereas δ_{it} measures the idiosyncratic distance between the common factor and the systematic part of X_{it}.

To test club convergence, Phillips and Sul (2007) estimate the following *log-t* regression:

$$\log\left(\frac{H_1}{H_t}\right) - 2\log L(t) = a + b\log t + u_t$$

Where $\frac{H_1}{H_t}$ is the cross-sectional variation ratio: H_1 is the cross-sectional variance at $t = 1$ while $H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it} - 1)^2$ is the cross-sectional variance at t with $h_{it} = \frac{X_{it}}{\frac{1}{N}\sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{\frac{1}{N}\sum_{i=1}^{N}\delta_{it}}$.

$L(t) = \log\ (t+1)$ denotes the slowly varying function (penalty function) over time.

Phillips and Sul (2007) suggest dropping the first third of the sample when starting the estimation. If the *t*-statistic of the estimated coefficient $\hat{b}$ is less than -1.65 (at 5% significance level), the null hypothesis of convergence is rejected. Given this outcome, their data-driven clustering algorithm determines the possible convergence clubs.

C. The ordered logit model

To further inspect the factors that determine the sorting into different convergence clubs, we estimate an ordered logit model where the dependent variable is an ordinal variable reflecting the ordered club numbers from the lowest club classification (club 11 is assigned y=0) to the highest club classification (y=10 for club 1). This allows us to say something about the relevant factors that may lead a region to converge to a higher or lower TFP convergence club. The ordered logit model uses the maximum likelihood estimator. The independent variables are the initial values of factors identified by the empirical literature to matter for regional TFP. These include proxies for infrastructure density, R&D, human capital, the structure of the labor market and geographic factors, that are presented in the next sub-section. The literature has invariably demonstrated the positive impact of human capital on TFP (Marrocu and Paci, 2011; Dettori et al., 2012, Männasoo et al., 2018). In the same vein, Barrios et al. (2019) highlight the role of regional R&D resources in shaping the regional knowledge production and absorption capacities. Further, R&D is shown to be a major determinant of TFP (Danska-Borsiak, 2018; Kijek and Matras-Bolibok, 2019). Furthermore, an important structural aspect of an economy is employment in knowledge intensive sectors (Kijek et al., 2022). Indeed, differences in industrial and services structures are likely to shape long-term innovativeness (Kijek and Matras-Bolibok, 2018). The literature has also highlighted the positive repercussion of physical infrastructure on productivity (Zhang and Ji, 2019). Lastly, agglomeration economies can positively affect regional TFP (Escribá-Peréz and Murgui-García, 2014). We also include a set of country dummies to control for country-level factors such as the quality of institutions effects (Bartkowska and Riedl, 2012; Barrios et al., 2019), and cluster the standard errors by country since TFP clustering within countries is very likely.

D. Sample and data

The data is collected for 1995-2018 and for a sample of 155 NUTS regions. We follow the recommendation of Paci (1997) and select NUTS regions with administrative and policy functionality, capable of implementing measures with possible implications on their productivity level. Consequently, following Marrocu and Paci (2011), Kijek, and Matras-Bolibok (2019), and Kijek et al. (2023), we consider a mix of NUTS 1 and 2 regions. The list of countries and regions is in Appendix A[9]. To estimate the production functions, we extract from Cambridge Econometrics database total employment ("Temp2"), gross domestic product at constant prices ("ROVGD2"), and gross fixed capital formation at constant prices ("GFCFeuro2")[10]. To construct the capital stock, we employ the perpetual inventory method (see Appendix B). To estimate the ordered logit model, we use the following variables: the percentage of the population aged 25-64 that reached a tertiary education level (levels 5 to 8), the length of motorways per square kilometer, the per capita spending on R&D, the share of employment in high-tech sectors in total employment, and the population density (measured as the size of the population per square kilometer). The variables are extracted from two databases: the Eurostat regional database and the OECD regional database.

IV. Club Convergence: Results of the PS Test and the Logistic Regression

A. TFP-convergence clubs

When considering the entire sample, the *log-t* test rejects the null hypothesis of overall regional convergence to a unique equilibrium (t-stat= -97.733 < critical value -1.65 at the 5% significance level). In light of the absence of TFP convergence across the complete sample, the test initially identifies twenty convergence clubs and one diverging club, which shows

9) All appendices are part of the supplementary material.

10) Pesaran (2015) and Pesaran (2007) tests show respectively that the variables used to estimate the production functions are cross-sectionally dependent and nonstationary. Results can be provided upon request. Appendix C lays out the results of estimating equation (2).

evidence in favor of club convergence and the presence of multiple equilibria[11]. This is in line with several papers testing the prevalence of convergence clubs among European regions (Barrios et al., 2019; Kijek et al. 2022; Kijek et al., 2023). In order to check if some of the initially identified clubs show joint convergence and can therefore be merged, we run the clustering algorithm and reapply the *log-t* test to eventually merge the clubs that exhibit convergence collectively. We identify a final set of eleven convergence clubs and one divergence group as shown in Table 1.

Table 1. *Convergence Clubs*

Club	Member Regions	$\hat{b}$ (t-stat)	Average TFP over the period
Full Sample	--	-0.811(-97.733*)	-
Club 1 [2]	DE2, DEA	1.615 (0.543)	27.065
Club 2 [4]	DE1, DK, FR1, SE	0.815 (6.686)	26.631
Club 3 [4]	DE9, UKG, UKH, UKJ	0.337 (9.304)	26.104
Club 4 [34]	BE2, DE3, DE7, DEB, DED, ES30, ES51, ES61, FI1, FRE, FRF, FRI, FRJ, FRK, FRL, IE0, ITC1, ITH3, ITH5, ITI1, ITI4, NL32, NL33, NL41, PL41, PL92, PT1, RO, UKC, UKD, UKE, UKF, UKK, UKM	-0.055 (-1.388)	25.498
Club 5 [25]	AT13, BE3, BG, CZ, DE4, DE6, DEE, DEF, DEG, EL30, ES11, ES21, ES52, FRB, FRC, FRD, FRG, FRH, HU1, ITF3, ITG1, PL21, PL91, UKL, UKN	0.025 (0.513)	24.885
Club 6 [42]	AT22, AT31, AT33, AT34, BE1, DE5, DE8, DEC, ES24, ES41, ES42, ES53, ES62, ES70, HR, ITC3, ITF1, ITF4, ITITF6, ITITG2, ITH1, ITH2, ITH4, ITI3, LU, NL21, NL22, NL31, NL42, PL22, PL42, PL51, PL52, PL61, PL63, PL71, PL81, PL82, PL84, PT3, SI, SK	-0.017 (-0.403)	23.939
Club 7 [14]	AT12, AT21, AT32, CY, EE, EL52, ES12, ES22, ES43, ITF5, ITI2, LT, LV, NL11	0.292 (5.115)	23.553
Club 8 [6]	ES13, NL12, NL13, NL34, PL43, PL62	0.137 (2.736)	22.927
Club 9 [13]	AT11, EL43, EL51, EL61, EL63, EL64, EL65, ES23, ITF2, MT, NL23, PL72, PT2	0.197 (3.494)	22.614
Club 10 [3]	EL42, EL54, ITC2	1.992 (11.925)	22.095
Club 11 [2]	EL53, EL62	2.907 (7.967)	21.892
Non-converging Club 12 [6]	EL41, ES63, ES64, FRM, ITC4, UKI	-0.954 (-137.80*)	-

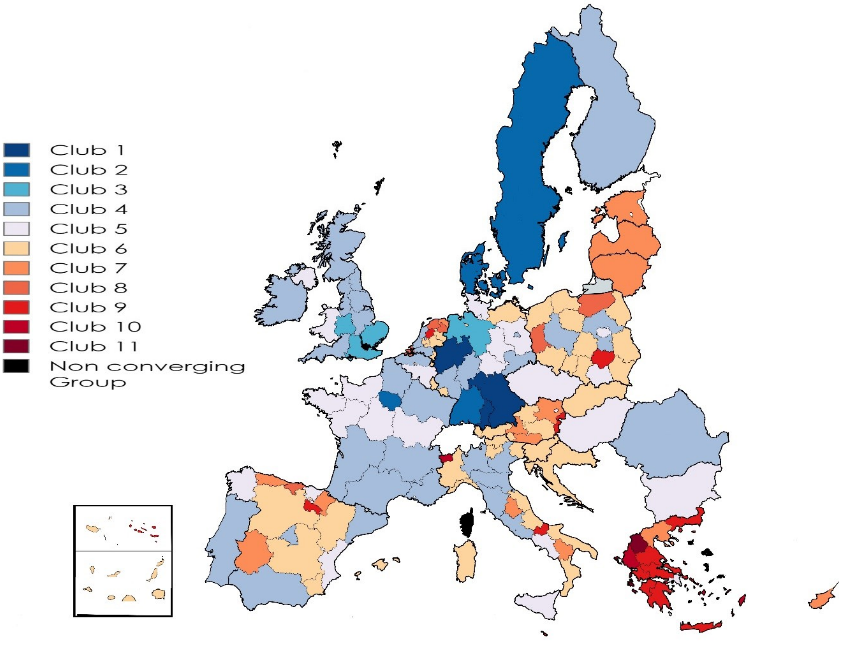
Note. i) * denotes the rejection of the null of convergence at the 5% significance level; ii) between parenthesis ( ) are the *log-t* statistics; iii) between brackets [] are the number of regions in each club.

Most of the clubs display conditional convergence (convergence in growth rates), as revealed by the estimated *b* coefficient whose value is less than 2 for 7 clubs (Phillips and Sul, 2009). Only two clubs exhibit absolute level convergence (with a value of 2 and above for the estimated

11) Results are available upon request. We prefer highlighting the findings of the "final classification" to save space.

b coefficient): clubs 10 and 11. Finally, clubs 4 and 6 display weaker convergence relative to the other clubs (with a negative value for $\hat{b}$). Interestingly, the latter clubs contain the largest number of regions from countries of different development levels and that adhered to the EU at different points in time. To make sense of our findings, Figure 2 depicts the spatial distribution of the identified convergence clubs.

Figure 2. Geographical distribution of the convergence clubs



Note. dark blue and dark brown represent respectively top performing TFP regions and low performing TFP regions.

Based on the results displayed in Table 1 and Figure 2, we can highlight a number of observations. First, the convergence clubs can be ranked according to their mean TFP over the period in a descending order: the first club has the highest mean TFP while the last one has the lowest average TFP. This is illustrated in Figure 2 through the spectrum of the blue and brown color shades: blue is used to illustrate the first five convergence clubs (with mean TFP greater than the overall sample mean), and brown to capture the remaining convergence clubs (with average TFP less than the sample average). Second, we note that, in several cases, the clubs tend to cluster spatially. In France, for instance, there is evidence of clustering among southern regions (club 4); in the northern part of the country, regions are broadly clustered in the eastern side on the one hand (club 4) and the western side on the other (club 5). Clustering is also evident in the United Kingdom with northern regions being part of club 4. This is also the case of southwestern regions, while southeastern regions are part of club 3[12]. Germany follows the same pattern: regions in the eastern part of the country are clustered in clubs with lower mean TFP values than their counterparts in the west. Third, many regions among the high-mean TFP convergence clubs are relatively populous and geographically large (e.g. Bavaria, North Rhine-Westphalia in Germany; Ile de France in France), include the capital city of the country (e.g. Berlin, Paris, Madrid, Warsaw), and constitute the economic center of the country with high-value added service sectors. On the other hand, several regions of the low-mean TFP convergence clubs are mostly mountainous and sparsely populated (e.g. Aosta valley in Italy, Asturias in Spain), largely dependent on tourism and the tourism-related services (e.g. Crete and Ionian islands in Greece), and mainly relying on agriculture and farming (e.g. Extremadura in Spain, Friesland in the Netherlands). Fourth, when looking at the distribution of convergence clubs across countries, we notice two marked lines of divide: a first one separating the "old" EU-member countries from the members that joined the Union after 2004, and another one differentiating among the old EU-member states between northern and western Europe on the one hand, and southern Europe on the other. When it comes to the first demarcation line, nearly 87 percent of the regions in high-TFP clubs (clubs 1 through 5) are located in old EU-member countries, whereas only around 13 percent of the regions of the top TFP clubs are situated in new member states[13]. Moreover, while almost half of the regions of old member states appear in low-TFP clubs (club 6 through 11), around 72 percent of the regions in new member states are part of the latter clubs. Regarding the second divide, nearly 63 percent of the regions in high-TFP clubs are from old EU-member countries located in northern/western Europe, whilst merely 24 percent of the regions in the latter clubs are from old member states situated in southern Europe. Furthermore, while only 36 percent of the regions situated in northern/western European countries are members of low-TFP clubs, around 71 percent of the regions located in southern European countries are part of the latter clubs.

Comparing our findings to Kijek et al. (2023), the only paper that applies the PS method on NUTS regional TFP series, we note the following. Similar to Kijek et al. (2023), we find evidence of club convergence in productivity among European regions, with most of the top performing ones located in western and northern Europe. However, unlike Kijek et al. (2023) who found Italian regions to be part of the convergence club with the highest TFP level, our analysis shows that most of the Italian regions are members of the clubs with the lowest TFP values. In addition, while regions from eastern European countries are concentrated in the low-TFP club in Kijek et al. (2023), we find that the latter regions are scattered across several clubs, albeit mostly among low-TFP clubs.

12) With the exception of "Greater London" which is part of the group that is non-converging.

13) Old European countries are: Austria, Belgium, Denmark, France, Finland, Germany, Greece, Luxembourg, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom. New member states are: Bulgaria, Croatia, Cyprus, Czechia, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, and Slovenia.

B. Club-membership: Key conditioning factors

We present the coefficients from estimating the ordered logit model in Table 2 along with the marginal effects (at the mean values) of the variables that are found to matter for the convergence clubs. Marginal effects measure the instantaneous rate of change in the probability of belonging to a specific club due to a small change in the independent variables. In this exercise, we merge the top three TFP clubs and the bottom 4 clubs to improve identification due to the low number of regions in some clubs. Summary statistics of the explanatory variables across the identified clubs are provided in Appendix D. The results suggest that the probability of membership in clubs 5 and up can be partially explained by R&D spending and the percentage of the labor force working in the high-tech sector[14]. Our findings echo the results of Kijek et al. (2023) who demonstrate the importance of innovation and scientific research for high-TFP club membership. Marginal effects suggest that a small positive change in R&D and the percentage of the labor force in the high-tech sector increases the probability of belonging to the more productive clubs, while it decreases the probability of belonging to the less innovative clubs (Clubs 6 to 11). The magnitude of the coefficients as well as the marginal effects are not too different across the two variables.

Table 2. *Results of the ordered logit model*

	Ordered Logit	Marginal Effects					
		Club 1,2,3	Club 4	Club 5	Club 6	Club 7	Club 8,9,10,11
Infrastructure	-0.302 (0.852)						
R&D spending	1.74*** (0.367)	0.009 (0.008)	0.231*** (0.059)	0.195** (0.083)	-0.343*** (0.079)	-0.066*** (0.024)	-0.025* (0.014)
Skilled labor %	-0.596 (1.517)						
High tech labor %	2.107*** (0.706)	0.011 (0.009)	0.279*** (0.083)	0.236* (0.128)	-0.415*** (0.142)	-0.080** (0.037)	-0.031* (0.018)
Pop. density	0.585 (0.630)						
N	134						

Note. i) the dependent variable is the ordered number of convergence clubs (from lowest mean TFP to highest); ii) marginal effects are only reported for the estimated coefficients that are found to be statistically significant; iii) the regression contains country dummies whose estimated coefficients are not listed for the sake of brevity; iv) ***p < 0.01, **p < 0.05, *p < 0.1; v) standard errors are clustered by country.

14) Using regional patent stock as an alternative measure for R&D returns similar results.

V. Club convergence: A closer look

A. The case of regions in "old" EU-member countries of southern Europe

The case of regional TFP in old member states of southern Europe is noteworthy. Indeed, this bloc registered the lowest mean regional TFP (23.35), well below the overall sample mean. Moreover, the same bloc experienced a sluggish average annual TFP growth rate (0.037 percent), the lowest among all blocs and significantly below the sample mean. Appendix E demonstrates a comparison between the mean TFP/TFP growth of these regions, the regions of north and western Europe, and the regions in the new member states.

To explore this further, Figure 3 depicts the TFP time path of each region in the relevant countries, relative to the total sample mean. That is, it traces the following ratio ("relative transition path", Phillips and Sul (2009)) at every year across the covered period[15]:

$$h_{it} = \frac{TFP_{it}}{N^{-1}\Sigma_{i=1}^{N} TFP_{it}} \qquad (t = 1996, \ldots, \ 2018)$$

The figure reveals that the poor performance of this group of regions is chiefly due to Greek regions and, to a lesser extent, Italian ones. Indeed, almost all the Greek regions experienced a downward relative transition path, typically starting from a low initial point (compared to "1" which indicates a TFP equal to the sample mean). This is corroborated by a negative average annual growth rate of regional TFP in Greece (-0.02 percent) and a meager rate in Italy (0.02 percent) over 1996-2018. In fact, as shown in Table 1, many Greek and Italian regions are members of the lowest ranked TFP convergence clubs. Moreover, it seems that the 2007/8 global financial crisis along with the 2011 euro-debt crisis had an adverse impact on regional productivity in Greece and Italy. In addition, several Greek and Italian regions seem to be on a "divergence" track, with relative transition paths diverging relative to mean TFP.

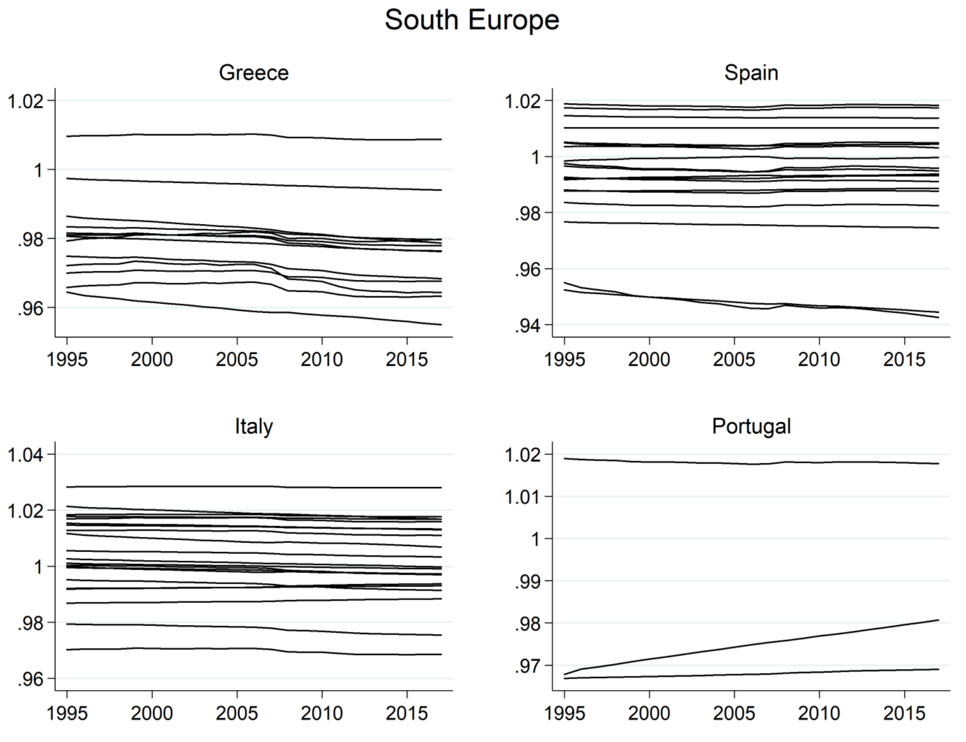
The poor performance of Greek and many Italian regions in terms of TFP echoes their negligible achievement in terms of the two significant conditioning factors of TFP club membership, namely employment in high-tech sectors and R&D. Indeed, besides the region that includes Athens (Attica), none of the Greek regions has an employment in high-tech sectors (as a share of total employment) greater than the sample mean. Moreover, no Greek region fares better than the sample mean in terms of per capita R&D spending, and per capita stock of patents.

15) The relative TFP transition paths of regions within each of the clubs are found in Appendix F. Similar to Kijek et al. (2023), the within-clubs transition paths take the form of a funnel, reflecting convergence. Interestingly, our time horizon allows us to pinpoint the adverse effect that the 2007/08 crisis had on several transition paths, notably in the case of clubs 9, 10, and 11. Given their time span that starts in 2008, detecting the impact of the 2007/8 crisis on the pre-crisis long-term trend of the transition paths was not possible in Kijek et al. (2023).

Similarly, few Italian regions do better than the sample average across the employment in high-tech and R&D measures.

The regions that are among the low-TFP convergence clubs face the risk of remaining there and falling in a "productivity trap". In view of the importance of TFP for the overall economic performance, this is likely to have important repercussions on the regional economies in these countries. Moreover, given the significance of convergence in productivity for the income convergence dynamic across EU-member states and regions, the risk of many regions falling in a productivity trap could imperil the Union's efforts for strengthening coherence across member countries and regions.

Figure 3. Relative transition TFP paths of regions in old EU-member countries located in southern Europe to the EU regional average

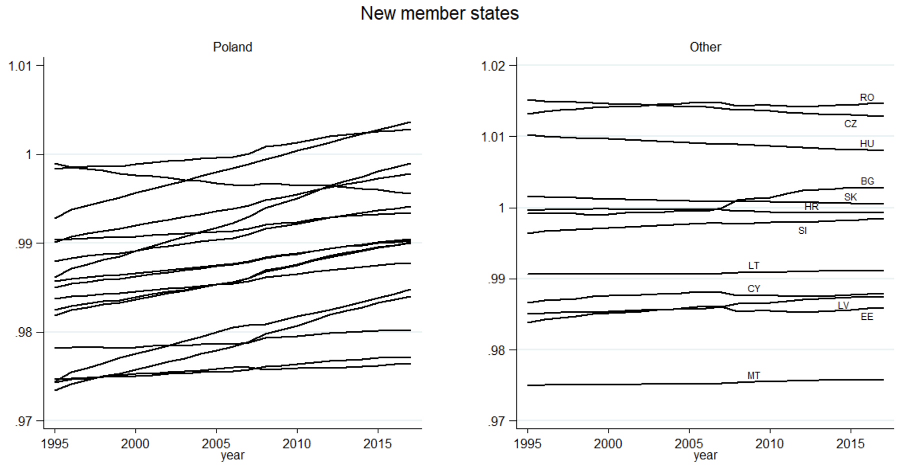


B. The case of regions in new EU-member states

As for the regions of the new EU member states, although their mean TFP value (23.98) is less than the sample mean, it increased over the period at a relatively fast pace: the regional annual mean TFP growth for the bloc of new EU-member states is the largest in the sample. The substantial increase in productivity in this group of regions is mainly due to the TFP growth rates in the regions of Poland; indeed, with a mean annual growth rate of 0.118 percent, Poland registered the largest regional productivity growth among the new EU-member states.

Figure 4 shows the transition paths of the TFP of the regions of the new member states relative to the EU regional TFP average. Poland is exhibited in the left panel of the graph and shows that most regions show convergence to the EU regional TFP average, albeit at different rates. It is noteworthy that the financial crisis of 2007/8 does not seem to have affected convergence. If anything, it seems to have enhanced convergence in some instances. In the right panel, the remaining countries that joined the EU from 2004 are exhibited. The picture that emerges is a mixed one. Malta, Cyprus, and the Baltic States demonstrate a lack of convergence, whereas the new member countries in central Europe (Czechia, Hungary, and Slovakia) and eastern and southern Europe (Croatia, Bulgaria, Romania, and Slovenia) converge to the EU regional average. Overall, European integration and cohesion seems to have succeeded in bringing most of the regions of the new member states up to the EU regional average - something that we do not see for some of the south European regions as we discussed above, a testament of at least partial success of the EU cohesion policies over the past few decades.

Figure 4. Relative transition TFP paths of the new member states to the EU regional average



VI. Policy Recommendations and Possible Extensions

The present analysis suggests the clustering of NUTS regions across TFP convergence clubs. Perhaps the most alarming insight of our investigation is the case of many regions in southern Europe that face a risk of falling in a productivity trap and remaining in low-TFP clubs. In view of the importance of the role played by TFP in driving growth and lessening economic disparities, and given the recent policy emphasis on fostering innovation and productivity among EU-members and regions in the EU agenda, a number of recommendations are in order.

Firstly, there is a need to prioritize the regions lagging behind, especially those potentially falling in a productivity trap that would further reduce their development prospects. In this regard, the Catching-up Regions Initiative seems to be a suitable framework to assist the lagging regions[16]. It is, however, important to reframe this initiative for a better outcome. In particular, it is imperative to rightly channel the provided funding: over the past years, the initiative's main focus was regions in eastern Europe with a relative neglect of regions in southern Europe. Secondly, an approach that would simply rely on funneling additional funds to the lagging regions is likely to be inefficient if not coupled with a holistic vision that would also address regional shortages hindering TFP growth. The Cohesion Policy should thus adopt an encompassing approach bridging interventions in several domains in a single coherent framework. Thirdly, the needs of the trailing regions are location-specific. For instance, some regions might primarily lack an appropriate infrastructure while others may mostly suffer from insufficient R&D resources. Consequently, a location-based approach is likely to be more successful than a top-down/one-size-fits-all approach. Fourthly, strengthening interregional cooperation between the best performing regions and the ones left behind, especially in terms of innovation and R&D, is advocated. This would stimulate productivity in low-TFP clubs through technological advancement, entrepreneurship, and knowledge transfer. Lastly, in some cases, especially in Greece and Italy, a significant proportion of the regions are poor performers when it comes to TFP. In such cases, a closely coordinated multi-level intervention scheme, involving regional as well as national authorities, might be the best design to ensure optimal results in terms of enhancing productivity.

The present analysis can be extended in at least two directions. Firstly, the last year covered in our empirical analysis is 2018 for data availability reasons[17]. Once more recent data becomes available, it would be possible to further stretch the investigation in time. This will allow researchers to examine the effects of the post-2018 period shocks (notably the Covid-19 pandemic) on the convergence process. Secondly, our research identifies a number of regions that are excessively trailing in TFP. Another possible extension of the present research would undertake a thorough investigation of the factors that would explain the meager performance of the lagging regions.

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16) The Catching-up Regions Initiative is an EU policy framework aimed at accelerating the development and economic convergence of less developed regions within the Union. It is a crucial component of the EU's Cohesion Policy, providing an intensified, tailored focus on the most underdeveloped regions. By doing so, it enhances the overall effectiveness of the Cohesion Policy in reducing regional disparities and promoting balanced and inclusive development across the EU.

17) Data used to estimate the production functions is available up to 2022. However, the 2019-2022 figures are predicted based on the 2015-2018 trend. Given the significant effect of the Covid-19 pandemic, it is very likely that the forecast is off the mark; we thus did not use the 2019-2022 projected values.

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Appendix A. Sample of Countries, NUTS Regions, and NUTS Levels

Country	Region code	NUTS level	Name of the region
Austria	AT11	2	AT11: Burgenland
Austria	AT12	2	AT12: Lower Austria
Austria	AT13	2	AT13: Vienna
Austria	AT21	2	AT21: Carinthia
Austria	AT22	2	AT22: Styria
Austria	AT31	2	AT31: Upper Austria
Austria	AT32	2	AT32: Salzburg
Austria	AT33	2	AT33: Tyrol
Austria	AT34	2	AT34: Vorarlberg
Belgium	BE1	1	BE1 Brussels Capital Region
Belgium	BE2	1	BE2 Flemish Region
Belgium	BE3	1	BE3 Wallonia
Bulgaria	BG	0	BGR: Bulgaria
Cyprus	CY0	0-1	Cyprus
Czechia	CZ	0-1	CZE: Czech Republic
Germany	DE1	1	DE1: Baden-Württemberg
Germany	DE2	1	DE2: Bavaria
Germany	DE3	1	DE3: Berlin
Germany	DE4	1	DE4: Brandenburg
Germany	DE5	1	DE5: Bremen
Germany	DE6	1	DE6: Hamburg
Germany	DE7	1	DE7: Hesse
Germany	DE8	1	DE8: Mecklenburg-Vorpommern
Germany	DE9	1	DE9: Lower Saxony
Germany	DEA	1	DEA: North Rhine-Westphalia
Germany	DEB	1	DEB: Rhineland-Palatinate
Germany	DEC	1	DEC: Saarland
Germany	DED	1	DED: Saxony
Germany	DEE	1	DEE: Saxony-Anhalt
Germany	DEF	1	DEF: Schleswig-Holstein
Germany	DEG	1	DEG: Thuringia
Denmark	DK0	0-1	DNK: Denmark
Estonia	EE0	1	EST: Estonia
Greece	EL30	2	EL30: Attica
Greece	EL41	2	EL41: North Aegean
Greece	EL42	2	EL42: South Aegean
Greece	EL43	2	EL43: Crete
Greece	EL51	2	EL51: Eastern Macedonia, Thrace

Country	Region code	NUTS level	Name of the region
Greece	EL52	2	EL52: Central Macedonia
Greece	EL53	2	EL53: Western Macedonia
Greece	EL54	2	EL54: Epirus
Greece	EL61	2	EL61: Thessaly
Greece	EL62	2	EL62: Ionian Islands
Greece	EL63	2	EL63: Western Greece
Greece	EL64	2	EL64: Central Greece
Greece	EL65	2	EL65: Peloponnese
Spain	ES11	2	ES11: Galicia
Spain	ES12	2	ES12: Asturias
Spain	ES13	2	ES13: Cantabria
Spain	ES21	2	ES21: Basque Country
pain	ES22	2	ES22: Navarra
Spain	ES23	2	ES23: La Rioja
Spain	ES24	2	ES24: Aragon
Spain	ES30	2	ES30: Madrid
Spain	ES41	2	ES41: Castile and León
Spain	ES42	2	ES42: Castile-La Mancha
Spain	ES43	2	ES43: Extremadura
Spain	ES51	2	ES51: Catalonia
Spain	ES52	2	ES52: Valencia
Spain	ES53	2	ES53: Balearic Islands
Spain	ES61	2	ES61: Andalusia
Spain	ES62	2	ES62: Murcia
Spain	ES63	2	ES63: Ceuta
Spain	ES64	2	ES64: Melilla
Spain	ES70	2	ES70: Canary Islands
Finland	FI1	0-1	Finland
France	FR1	1	FR1: Île-de-France
France	FRB	1	FRB: Centre - Val de Loire
France	FRC	1	FRC: Bourgogne-Franche-Comté
France	FRD	1	FRD: Normandy
France	FRE	1	FRE: Hauts-de-France
France	FRF	1	FRF: Grand Est
France	FRG	1	FRG: Pays de la Loire
France	FRH	1	FRH: Brittany
France	FRI	1	FRI: Nouvelle-Aquitaine
France	FRJ	1	FRJ: Occitanie
France	FRK	1	FRK: Auvergne-Rhône-Alpes
France	FRL	1	FRL: Provence-Alpes-Côte d’Azur
France	FRM	1	FRM: Corsica

Country	Region code	NUTS level	Name of the region
Croatia	HR	0-1	Croatia
Hungary	HU	0	HUN: Hungary
Ireland	IE0	1	IRL: Ireland
Italy	ITC1	2	ITC1: Piedmont
Italy	ITC2	2	ITC2: Aosta Valley
Italy	ITC3	2	ITC3: Liguria
Italy	ITC4	2	ITC4: Lombardy
Italy	ITF1	2	ITF1: Abruzzo
Italy	ITF2	2	ITF2: Molise
Italy	ITF3	2	ITF3: Campania
Italy	ITF4	2	ITF4: Apulia
Italy	ITF5	2	ITF5: Basilicata
Italy	ITF6	2	ITF6: Calabria
Italy	ITG1	2	ITG1: Sicily
Italy	ITG2	2	ITG2: Sardinia
Italy	ITH1	2	ITH1: Province of Bolzano-Bozen
Italy	ITH2	2	ITH2: Province of Trento
Italy	ITH3	2	ITH3: Veneto
Italy	ITH4	2	ITH4: Friuli-Venezia Giulia
Italy	ITH5	2	ITH5: Emilia-Romagna
Italy	ITI1	2	ITI1: Tuscany
Italy	ITI2	2	ITI2: Umbria
Italy	ITI3	2	ITI3: Marche
Italy	ITI4	2	ITI4: Lazio
Lithuania	LT	0-1	LTU: Lithuania
Luxembourg	LU0	1	LUX: Luxembourg
Latvia	LV0	1	LVA: Latvia
Malta	MT0	1	MLT: Malta
Netherlands	NL11	2	NL11: Groningen
Netherlands	NL12	2	NL12: Friesland
Netherlands	NL13	2	NL13: Drenthe
Netherlands	NL21	2	NL21: Overijssel
Netherlands	NL22	2	NL22: Gelderland
Netherlands	NL23	2	NL23: Flevoland
Netherlands	NL31	2	NL31: Utrecht
Netherlands	NL32	2	NL32: North Holland
Netherlands	NL33	2	NL33: South Holland
Netherlands	NL34	2	NL34: Zeeland
Netherlands	NL41	2	NL41: North Brabant
Netherlands	NL42	2	NL42: Limburg
Poland	PL21	2	PL21: Lesser Poland

Country	Region code	NUTS level	Name of the region
Poland	PL22	2	PL22: Silesia
Poland	PL41	2	PL41: Greater Poland
Poland	PL42	2	PL42: West Pomerania
Poland	PL43	2	PL43: Lubusz
Poland	PL51	2	PL51: Lower Silesia
Poland	PL52	2	PL52: Opole region
Poland	PL61	2	PL61: Kuyavian-Pomerania
Poland	PL62	2	PL62: Warmian-Masuria
Poland	PL63	2	PL63: Pomerania
Poland	PL71	2	PL71: Lodzkie
Poland	PL72	2	PL72: Swietokrzyskie
Poland	PL81	2	PL81: Lublin Province
Poland	PL82	2	PL82: Podkarpacia
Poland	PL84	2	PL84: Podlaskie
Poland	PL91	2	PL91: Warsaw's capital city
Poland	PL92	2	PL92: Mazowiecki region
Portugal	PT1	1	Portugal
Portugal	PT2	1	PT20: Autonomous Region of the Azores
Portugal	PT3	1	PT30: Autonomous Region of Madeira
Romania	RO	0	ROU: Romania
Sweden	SE	0	SWE: Sweden
Slovenia	SI	1	SVN: Slovenia
Slovakia	SK	0-1	SVK: Slovak Republic
United Kingdom	UKC	1	UKC: North East England
United Kingdom	UKD	1	UKD: North West England
United Kingdom	UKE	1	UKE: Yorkshire and The Humber
United Kingdom	UKF	1	UKF: East Midlands
United Kingdom	UKG	1	UKG: West Midlands
United Kingdom	UKH	1	UKH: East of England
United Kingdom	UKI	1	UKI: Greater London
United Kingdom	UKJ	1	UKJ: South East England
United Kingdom	UKK	1	UKK: South West England
United Kingdom	UKL	1	UKL: Wales
United Kingdom	UKM	1	UKM: Scotland
United Kingdom	UKN	1	UKN: Northern Ireland

Note. "0-1" refers to countries (NUTS-0) that are also classified as a NUTS-1 region (the country is too small - in terms of the population - to be divided into NUTS-1 regions).

Appendix B. Construction of Capital Stock Series

We construct the stock of capital in the initial year (k_0) as follows:

$$k_0 = \frac{I_0}{(growth\ rate\ of\ investment + depreciation\ rate)}$$

Where initial year investment (I_0) is measured using the gross fixed capita formation (GFCF). For most regions the initial year was 1980; for regions with missing 1980 data, we considered the closest year to 1980 as the initial year. The selection of 1980 as the initial year falls significantly behind 1995 (the starting year of our production function estimations), thus cushioning the repercussions of the initial year stock of capital on the 1995 (and following) capital stock values. We employed the average annual growth rate of GFCF over the first 7 years of available observations as the growth rate of investment. Depreciation rate is set equal to 10%. We also used a 15% depreciation rate as a robustness check. Capital stock in subsequent years is calculated using the perpetual inventory method:

$$k_t = k_{t-1} \times (1 - depreciation\ rate) + I_t$$

GFCF is extracted from Cambridge Econometrics database. In the latter, the data for the period 2019-2022 is predicted based on the 2015-2018 trend. Given the Covid-19 outbreak in 2019, it is likely that the 2019-2022 forecast is off the mark. Thus, we limited the estimation of the regional production functions and the derivation of the capital stock series to the period 1995-2018.

Appendix C. AMG Estimates of Equation (2)

Regressor	Estimated coefficient
L	0.608***(0.04)
K	0.122***(0.02)
CDP	0.757***(0.05)
Region trend	0.001(0.001)
Constant	13.346***(0.76)
Observations	3720
RMSE	0.02

Note. i) estimated coefficients are outlier-robust means; ii) between parentheses standard errors are constructed following Pesaran and Smith (1995) and test the statistical significance of the average coefficient (H0: $\frac{1}{N}\sum_i \hat{\beta}_i = 0$); iii) *** denotes significance at 1%; iv) "RMSE" refers to the root mean square error; v) *l* and *k* are in logs.

Appendix D. Summary Statistics of the Explanatory Variables of the Ordered Logit Model, by Convergence Club

Club 1

Variable	Obs	Mean	Std. Dev.	Min	Max
infrastructure	2	0.047	0.023	0.031	0.063
R&D spending	2	831.82	331.768	597.224	1066.415
Skilled labor %	2	21.2	2.687	19.3	23.1
High tech labor %	2	4.55	0.778	4	5.1
population density	2	347.349	250.744	170.047	524.652
TFP	2	26.769	0.255	26.588	26.949

Club 2

Variable	Obs	Mean	Std. Dev.	Min	Max
infrastructure	4	0.025	0.019	0.003	0.049
R&D spending	4	1212.516	387.147	711.71	1568.046
Skilled labor %	4	28.5	3.584	25.1	33
High tech labor %	4	6.75	1.207	5.5	8.4
population density	4	332.995	395.089	19.626	901.776
TFP	4	26.396	0.358	25.989	26.840

Club 3

Variable	Obs	Mean	Std. Dev.	Min	Max
infrastructure	4	0.026	0.009	0.013	0.033
R&D spending	4	724.134	327.535	361.587	1096.87
Skilled labor %	4	25.625	4.79	19.9	31.6
High tech labor %	4	6.075	2.442	3.3	8.9
population density	4	312.108	117.396	163.355	407.711
TFP	4	25.844	0.301	25.556	26.184

Club 4

Variable	Obs	Mean	Std. Dev.	Min	Max
infrastructure	33	0.029	0.024	0	0.088
R&D spending	32	499.529	302.652	79.12	1288.323
Skilled labor %	34	21.009	7.524	8.8	33.6
High tech labor %	34	4.359	1.523	1.5	7.2
population density	34	351.557	661.784	15.043	3892.599
TFP	34	25.344	0.575	23.093	26.045

Club 5

Variable	Obs	Mean	Std. Dev.	Min	Max
infrastructure	24	0.024	0.028	0	0.11
R&D spending	24	342.833	363.574	45.349	1697.744
Skilled labor %	25	21.26	8.548	8.9	48
High tech labor %	25	3.74	1.523	1.6	8.4
population density	25	423.233	829.451	56.776	3721.886
TFP	25	24.734	0.447	23.389	25.340

Club 6

Variable	Obs	Mean	Std. Dev.	Min	Max
infrastructure	42	0.024	0.031	0	0.12
R&D spending	37	346.989	344.432	30.851	1361.301
Skilled labor %	42	14.955	6.95	3.6	37
High tech labor %	41	2.998	1.146	1.1	6.3
population density	42	340.305	913.34	21.494	5848.994
TFP	42	23.749	0.711	21.785	25.045

Club 7

Variable	Obs	Mean	Std. Dev.	Min	Max
infrastructure	14	0.012	0.01	0	0.033
R&D spending	13	212.201	223.923	37.392	886.202
Skilled labor %	14	20.214	9.481	6.9	42.4
High tech labor %	14	2.686	1.271	1.2	5.1
population density	14	78.042	50.956	25.573	232.46
TFP	14	23.444	0.387	22.921	24.318

Club 8

Variable	Obs	Mean	Std. Dev.	Min	Max
infrastructure	6	0.019	0.016	0	0.036
R&D spending	6	140.175	94.402	29.535	236.136
Skilled labor %	6	16.233	5.131	10.3	23.4
High tech labor %	6	2.233	1.227	1.2	4
population density	6	124.459	54.104	60.49	189.847
TFP	6	22.825	0.381	22.265	23.304

Club 9

Variable	Obs	Mean	Std. Dev.	Min	Max
infrastructure	13	0.007	0.011	0	0.034
R&D spending	11	129.74	133.981	45.741	501.614
Skilled labor %	13	12.262	4.764	5.4	22.9
High tech labor %	12	2.483	2.075	0.9	7.2
population density	13	155.48	314.224	35.448	1197.481
TFP	13	22.528	0.347	21.719	23.117

Club 10

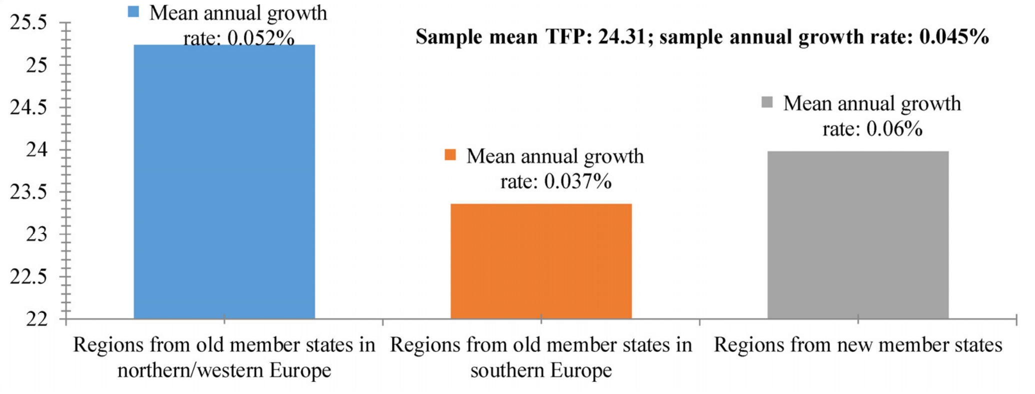
Variable	Obs	Mean	Std. Dev.	Min	Max
infrastructure	3	0.01	0.018	0	0.031
R&D spending	3	81.335	48.65	37.259	133.536
Skilled labor %	3	10.8	3.477	7.6	14.5
High tech labor %	3	2.033	1.185	1.3	3.4
population density	3	42.201	10.488	35.904	54.308
TFP	3	22.055	0.194	21.934	22.278

Club 11

Variable	Obs	Mean	Std. Dev.	Min	Max
infrastructure	2	0	0	0	0
R&D spending	2	31.912	7.418	26.666	37.157
Skilled labor %	2	12.75	0.636	12.3	13.2
High tech labor %	0				
population density	2	58.612	39.367	30.776	86.449
TFP	2	21.866	0.314	21.644	22.088

Note. summary statistics are computed across regions of a given club using data of the initial year.

Appendix E. Mean TFP and Annual Growth Rate of TFP (1996-2018) in Regions Located in the Old EU-Member Countries as Well as the New Member States



Note. i) regions from old member states in northern/western Europe are located in Austria, Belgium, Denmark, France, Finland, Germany, Sweden, and the United Kingdom; ii) regions from old member states in southern Europe are situated in Greece, Italy, Portugal, and Spain; iii) regions from new member states fall in Bulgaria, Croatia, Cyprus, Czechia, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, and Slovenia.

Appendix F. Relative Regional TFP Transition Paths across Convergence Clubs