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Revisiting TFP regional convergence in the EU

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Abstract

Using recent data on 155 NUTS (Nomenclature of Territorial Units for Statistics) regions across EU member states, we estimate region-specific production functions to generate regional TFP (Total Factor Productivity) series from 1996 to 2018. The empirical strategy we employ presents a number of desirable properties, as it is based on heterogeneous production functions and accommodates cross-sectional dependence and nonstationarity. We then apply panel unit root tests, some of which allow for structural breaks, to examine whether the European integration and expansion processes were accompanied with a convergence in productivity amongst NUTS regions. A number of results arise from our empirical analysis. First, there are significant disparities in terms of TFP across NUTS regions, with regions located in northern and western Europe typically showing the highest productivity levels and regions in eastern and southern Europe exhibiting the lowest levels. Second, the vast majority of the regions experienced an improvement in their productivity levels over the 23-year time span. The regions with the largest growth rates of productivity over the period are those located in eastern Europe. Third, a convergence dynamic was at play during the studied period. Indeed, findings show that regional TFP series converged towards the sample mean. Moreover, there is evidence that regional TFP of member states, who joined the EU 2004 onwards, converged to the mean TFP of the EU-12 member states.

JEL Classification: O47, O52.

Keywords: NUTS regions, EU, regional TFP, convergence, panel unit root tests.

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1 Introduction

The European Union (EU) is the largest and the most prominent economic integration project in modern history. In the past two decades, the EU expanded from 15 members before 2004, to 28 members in 2013. However, the expansion rounds were somewhat controversial because of the large economic differences that existed between some of the newcomers and the founding members. Acknowledging these disparities, one of the goals of the EU is to strengthen economic and social cohesion within the Union. A key mechanism to achieve this is through income convergence amongst the member states (Alcidi, 2019).

Fundamentally, income convergence implies that income gaps between countries narrow over time. Practically, it means that poorer countries grow faster than richer countries and, hence, a catch-up growth mechanism is in place (Alataş, 2021). In this respect, the theoretical and empirical literature suggests that disparities in technology, in general, and total factor productivity (TFP), in particular, are the main determinants of the rate of income convergence between countries (De la Fuente, 2002; Islam, 2003; Kijek, Kijek and Matras-Bolibok, 2023). Moreover, income disparities that remain unexplained, after controlling for differences in labour and capital stocks, are mainly attributed to discrepancies in productivity (Kijek and Matras Bolibok, 2020). Convergence in TFP is important because it means that the productive capacities of the converging economies are becoming closer to each other, which facilitates income convergence.

Many studies investigated technological convergence at the country level (Dowrick and Nguyen, 1989; Wolf, 1991; Mankiw, Romer and Weil, 1992; Dougherty and Jorgenson, 1997; Tebaldi, 2016; Rath and Akram, 2019; Alataş, 2021). However, research at the regional level is still modest. Recently, the question of technological convergence at the regional level gained traction amongst researchers and policymakers (Rodil-Marzábal and VenceDeza, 2020). Research suggests that TFP levels may differ across regions because of non-transferable territorial or place-based components, like the geographic location of the region, its climate, or its endowment in natural resources (De la Fuente, 2002; Kijek, Kijek and Matras-Bolibok, 2023).

From this perspective, each region demands specific policies to stimulate productivity. In the context of the EU, the European Commission - the executive arm of the EU - carried out a number of policy measures, most notably the Cohesion Policy, that aim to reduce economic and social disparities amongst EU regions. The objective is to encourage investment, growth and employment in the less developed regions of the EU (Beugelsdijk, Klasing and Milionis, 2018; Kilroy and Ganau, 2020; Monfort, 2020). This policy is delivered through specific funds, such as the European Regional Development Fund (ERDF) and the Cohesion Fund (CF).⁴ Concurrently, the EU has policies in place with the specific purpose of fostering growth and job creation through innovation, technology diffusion, and the knowledge-based economy. Namely, the Lisbon Strategy and its successor, Europe 2020,

⁴ According to the European Commission website, the Cohesion Policy is delivered through four funds. These are: the European Regional Development Fund, the Cohesion Fund, the European Social Fund Plus, and the Just Transition Fund. Source: https://ec.europa.eu/regional_policy/policy.

were implemented from 2000 to 2020, with the overarching goal to make the EU regions the most competitive in the world through a combination of economic reforms, investment in research and innovation, and the promotion of entrepreneurship and employment (Hervás Soriano and Mulatero, 2010). These policies were put in place with the backdrop of the disparities that exist amongst the member countries and their regions. The disparities were exacerbated after the EU embarked on a major enlargement project in 2004 by admitting 10 new countries to the Union (with further expansions in 2007 and 2013). The new set of countries increased economic heterogeneity within the EU.

Examining convergence in TFP amongst EU regions is, therefore, warranted, especially in view of the objectives of the Cohesion Policy outlined above and the importance it attaches to technological progress. This is all the more important given the relative scantiness of the literature looking into TFP convergence amongst EU regions. Hence, the goal of our paper is to revisit TFP convergence amongst EU regions. Our methodology consists of two steps. First, we generate regional TFP time series for the EU NUTS regions over the 1996-2018 period, using a novel method proposed by Eberhardt and Teal (2020).⁵ Second, using the twopanel unit-root (PUR) tests of Levin, Lin and Chu (2002) and Karavias and Tzavalis (2014), we investigate whether TFP convergence, across the EU regions, to the EU's regional average occurs between 1996 and 2018. We similarly test regional convergence of TFP for the sample of newer member regions, who joined the Union in and after 2004, to the regional average of the core EU countries.

Three key findings emerge from our empirical investigation. First, the generated TFP series reveal significant regional disparities. Generally, regions that exhibit the highest TFP levels are located in northern and western Europe, whereas regions with the lowest TFP are in eastern and southern Europe. In the same vein, large productivity imbalances across regions within the same country are evident in the case of several countries. Second, the vast majority of the NUTS regions have experienced an increase in their productivity over the 23-year time span. Interestingly, the largest growth rates in productivity were registered in regions located in Eastern Europe. This hints to a catch-up process in productivity. Third, we find support for the hypothesis of convergence of regional TFP to the EU regional average and the convergence of TFP in the new members' regions to the EU-12 regional average, when no breaks in the series are assumed. We also find support for convergence in some or all the aforementioned series, when one or two breaks are assumed.

The contribution of this study is multifold. First, we implement the method of Eberhardt and Teal (2020) to generate EU regional TFP series. This method has the advantage over others of allowing for heterogeneous production functions, whilst accounting for cross-sectional dependence and non-stationarity. As far as we are aware, we are the first to use this method in the EU TFP regional convergence context. Second, we use the generated TFP series to test for stochastic convergence in EU regional TFP. Whilst we are aware of one other study that tests for TFP stochastic convergence in EU regions (Kijek, Kijek and Matras-Bolibok, 2023), our study chooses different PUR tests, one of which is that of Karavias and

⁵ NUTS stands for "Nomenclature of territorial units for statistics". It is a geographical classification that divides the economic territory of the EU into regions at three different levels: NUTS1, NUTS2 and NUTS3. In this paper we adopt the NUTS 2016 classification which replaced the 2013 classification.

Tzavalis (2014). This test allows for structural breaks, something that is contextual to the EU, in light of the multiple shocks that have impacted the region over our sample period, including the global financial crisis in 2007/8 and the sovereign debt crisis of 2011-2014. Third, our sample period (1996-2018) covers the most recent enlargements of the EU, including the major enlargement of 2004. In this regard, we are the first to examine whether regional productivity in the most recent EU member states converged to regional productivity in EU-12 member states. Moreover, our period covers fully or partially the different programming periods of the European Regional Development Policy (ERDP): 2000-2006, 2007-2013 and 2014-2020. To the best of our knowledge, our study is the only one that investigates EU regional TFP convergence over a long period, covering these crucial milestones in EU history. Finally, in view of the key role played by TFP in income convergence amongst EU regions/member states, our generated regional TFP measures can be highly informative to policymakers. Indeed, our findings provide new insights into the patterns of the spatial dispersion of TFP and its time evolution over a long period. In particular, our results identify the laggards and the leading regions in productivity. They also identify the regions that experienced the fastest TFP growth rates and those with the most sluggish growth.

The paper proceeds as follows. Section 2 provides an overview of the literature. The focus is on the methodologies commonly used to derive TFP measures, notably in a panel context. This section also reviews the literature that studied convergence amongst European regions. Section 3 lays out the empirical strategy and the data used. Section 4 presents the key findings, in terms of regional productivity performances and convergence tests. Section 5 provides the conclusion.

2 Literature review

Various methodologies are considered in the literature when investigating regional TFP convergence. Methodological differences accrue from the TFP derivation methods and the types of investigated convergence. In this section, we will discuss the different types of convergence and the derivation of the TFP series from growth regressions. We will only review studies related to the European regional context.

2.1 Regional TFP convergence/divergence dynamics

The concept of technological convergence is anchored in the research on income convergence, considered to be an implication of the neo-classical growth theory (Solow, 1956). The literature identifies four types of convergence (Kijek, Kijek and Matras-Bolibok, 2023). The first one is the β -convergence (absolute or conditional), which implies that economies with a 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 steady-state, β -convergence is said to be absolute. However, the steady-state depends on the economies' characteristics (namely the investment rate and the population growth rate). If

the level of technology in a given economy converges to a steady-state specific to that economy and determined by its structural characteristics, β -convergence is said to be conditional. The second one is the σ -convergence; it assumes a decreasing dispersion of technological progress across economies. The third one is the club convergence; it assumes multiple equilibria for groups of economies, depending on the attributes shared by them. To some extent, the club convergence is similar to the conditional convergence that assumes differences in the steady-states of technology across groups of economies. The last one is stochastic convergence; it focuses on the long-term behaviour of differences in technology across economies. In the presence of stochastic convergence, technological differences between economies should follow a stationary process. Overall, technological catch-up processes imply a flow of technological knowledge, from the more advanced to the less advanced economies. This shall reduce the technology gap between different economies.

Di Liberto and Usai (2013) investigate potential σ -convergence in TFP amongst 199 NUTS-2 regions in the EU-15, plus Norway and Switzerland. They find no evidence of TFP-convergence over the period 1985-2006. Using cross-sectional regressions, Escribá-Pérez and Murgui-García (2019) show that absolute and conditional β -convergence are present in the TFP of 121 NUTS-2 regions between 1995 and 2007. Kijek and Matras Bolibok (2020) estimate a panel regression model and find evidence for absolute β -convergence amongst 273 European regions (NUTS-2) for the period 2010-2016. Kijek, Kijek and Matras-Bolibok (2023) consider a sample of 219 European regions (NUTS-1 and NUTS-2) and test for three types of TFP convergence over the period 2008-2018: i) stochastic convergence, β -convergence, and club convergence. Their results support the presence of a convergence process amongst the EU regions. They find evidence for multiple equilibria amongst different clubs of regions. Furthermore, Siller et al. (2021) show a tendency for conditional β -convergence within 190 NUTS-1 and NUTS-2 regions between 1990 and 2014. Marrocu, Paci and Usai (2013) show evidence for conditional β -convergence amongst the TFP of 13 industries located in 276 European regions over the period 1996-2007. Finally, the results of Männasoo, Hein and Ruubel (2018) confirm the presence of conditional β -convergence in the TFP of 99 NUTS-1 regions between 2000 and 2013.

Other studies investigated the convergence in TFP amongst regions within one country. For example, Burda and Severgnini (2018) show persistent East-West TFP differences in Germany and TFP convergence until the mid-nineties. Byrne, Fazio and Piacentino (2009) show an absence of stochastic convergence in TFP for the Italian regions for the period 1970-2001.

In summary, the investigation of TFP convergence has, for the most part, suggested convergence amongst the regions covered. This finding stands out across the various methods of TFP calculation and the convergence tests applied. In the next sub-section, we discuss the literature on regional TFP calculation.

2.2 Regional total factor productivity (TFP)

Prescott (1998) argues that there is no clear economic theory for TFP. In fact, TFP is an empirical concept rather than a theoretical one. Different techniques were used in

empirical works, in order to derive the level of TFP and its growth rate. These are: data envelopment analysis, free disposal Hull model, growth accounting, efficiency indices, growth regressions and stochastic frontier analysis (Carlaw and Lipsey, 2003; Del Gatto, Di Liberto and Petraglia 2011).

This part of the review discusses the growth regressions method. This practice derives the regional TFP level from a canonical log-linearised Cobb-Douglas production function, where a proxy for regional output (gross value added or regional GDP) is regressed on the regional stock of capital and the regional stock of labour or total employment. According to Schatzer et al. (2019), three approaches are usually considered when estimating the Cobb-Douglas production function. The first one is the residual-based approach (Berlemann and Wesselhoft, 2012; Capello and Lenzi, 2014; Männasoo, Hein and Ruubel 2018; Escribá-Pérez and Murgui-García, 2019). The second one is the pooled panel approach (Marrocu, Paci and Usai, 2013; Mitze, 2014). The third one is the fixed-effect (FE) approach, initially advanced by Islam (1995). The latter is closely linked to the methodology we adopt in our paper and will be discussed in what follows.

The standard FE approach models TFP levels as regional fixed effects. TFP in this case is a long-term equilibrium value that measures the mean efficiency level across regions and over time. The latter is unit-varying but time-invariant. In the context of the European regions, Marrocu and Paci (2011), Dettori, Marrocu and Paci (2012), Ladu (2012), Di Liberto and Usai (2013) and Männasoo, Hein and Ruubel (2018) used this approach to derive the TFP levels for a panel of NUTS regions. When estimating the production function, authors often applied methodologies accommodating a number of issues, notably the possible endogeneity of the regressors and the spatial interconnections. Dettori, Marrocu and Paci (2012) and Marrocu and Paci (2011) estimate a spatial lag model (SAR) using a two-stage least squares (2SLS) estimator. The SAR model controls for spatial dependence and models explicitly economic spillovers between regions. The 2SLS controls for potential endogeneity of the regressors. Ladu (2012) estimates a static panel model, using the group mean fully modified ordinary least squares (FMOLS) estimator, proposed by Pedroni (2001). The latter accounts for serial correlation effects and the endogeneity in the regressors. Furthermore, Di Liberto and Usai (2013) estimate a dynamic panel model using several estimators: the least squares dummy variable (LSDV) estimator, the LSDV with spatial error correction (SEM), the LSDV with the correction advocated by Kiviet (1995) and the generalised method of moments (GMM) estimator. Finally, Männasoo, Hein and Ruubel (2018) estimate a static panel model, using the Greene (2005) “true” random-effects (RE) model.

Marrocu and Paci (2012a, 2012b) extended the FE approach and derived TFP levels from regional fixed effects, time effects and a country-time dependent error term. Their procedure continues to consider the fixed effects as long-term region-specific TFP levels but allows for temporal changes in TFP levels, caused by shocks common to all regions and captured by the time effects. Those shocks are assumed to affect all regions equally. The errors capture the regional deviations of TFP. They estimate a static panel data model using the 2SLS estimator. Schatzer et al. (2019) and Siller et al. (2021) further expand the FE approach and compute regional TFP levels from the regional fixed effects, the time effects and a region-specific time trend. The latter represents the regional long-term TFP growth rate. Thus, in addition to shocks affecting all regions in a similar fashion, Schatzer et al.

(2019) and Siller et al. (2021) allow for region-specific TFP growth rates. Their construct to derive TFP levels is, therefore, based on the fixed effects and TFP evolution: a common evolution (time effects) and a unit-specific progression (region-specific time trend). In their estimation strategy, the authors use a 2SLS estimator with spatial error. Schatzer et al. (2019) showed that empirical strategies which model TFP of a given unit at a given point in time as a composite factor with three components – namely, a unit-based initial technology level (country/region effects), TFP evolution over time depicted by universal shocks (time effects) and an idiosyncratic TFP evolution (unit-specific time trend) - do not suffer from misspecification, unlike other approaches.

All the above studies are based on the assumption that the production function is the same for all sample regions. In view of the vast regional disparities, in terms of a number of factors that can affect regional production, one would expect significant differences in the production processes across regions. Therefore, the underlying assumption of an homogeneous production function seems particularly strong. In addition, whilst most of the reviewed papers adopted methodologies that tackled the possible endogeneity of the regressors and the spatial interdependence amongst regions, they discarded the likely nonstationarity of the data.

3 Empirical strategy and data

Two steps underlie our empirical strategy. In the first step, we estimate Cobb-Douglas production functions for 155 NUTS-regions over the period 1995-2018, in order to generate regional TFP estimates. Given that the estimation method is based upon a first-differencing process, the resulting TFP estimates span the 1996-2018 period. In the second step and using Levin, Lin and Chu (2002) and Karavias and Tzavalis (2014) PUR tests (hereafter respectively LLC and KT), we look into whether convergence in productivity was at play during the covered time period: first, amongst all European regions and, second, in light of the EU expansion that took place from 2004. In what follows, we describe the methodology used, as well as the data employed.

3.1 Estimating production functions and generating TFP measures

The literature review emphasised the importance of adopting empirical frameworks that would allow a flexible modelling of the evolution of TFP (Schatzer et al., 2019). It also stressed the significance of employing estimators that would account for cross-section dependence, nonstationarity of the variables, whilst allowing for unit-specific production functions. In view of this, we apply the methodology proposed by Eberhardt and Teal (2020) to extract our regional TFP series.

Similar to Schatzer et al. (2019), Eberhardt and Teal (2020) consider that the TFP of a given cross-sectional unit at a certain point in time consists of its original level, as well as

its evolution over time, although they suggest alternative measurements for both TFP components. In addition, their approach couches the production function in a common factor context and is based on unit-specific regressions. This allows for parameter heterogeneity across production functions. Furthermore, they apply the Augmented Mean Group (AMG) estimator, which is an addition to the family of mean group estimators (Pesaran and Smith, 1995). The novelty of the AMG is the augmentation of the production functions, with proxies of the unobserved factors underlying the TFP. Consequently, the AMG accommodates cross-section dependence and nonstationarity; two aspects that are notoriously common in macroeconomic data. Using the AMG estimator would, thus, tackle the possible endogeneity of the regressors, whilst avoiding spurious results. The procedure used to derive TFP can be summarised as follows.

For $i = 1, \dots, N$ cross-sectional units (region-country) and $t = 1, \dots, T$ years, the following synthesises the AMG-estimation procedure⁶:

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

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

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}), labour (l_{it}), capital (k_{it}) (all in natural logs), a set of year dummies (D_t), and u_{it} (a white noise). Year dummy estimates are assembled as they 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 TFP⁷. Stage 2 is a set of N region-specific regressions, whereupon parameter estimates are averaged across regions⁸. The region-based production functions are extended to include region-specific linear trends (t) and the estimated CDP from the previous stage⁹.

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

⁶ Our geographical unit of analysis is region-country_{*i*}. For simplicity, we use region_{*i*} instead of region-country_{*i*} throughout the text.

⁷ The CDP captures the mean progression of unobserved common factors. Thus, it incorporates shocks of universal nature impacting all sample units; an example would be the 2007/8 financial crisis.

⁸ 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.

⁹ The linear trends are supposed to reflect omitted idiosyncratic factors affecting GDP. The latter include, for instance, the quality of institutions.

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:

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

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, including TFP evolution.

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

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

Third, we compute initial year TFP:

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

where $l_{i,initial\ year}$ and $k_{i,initial\ year}$ are, respectively, labour and capital stock values of region i in the base year. Region-specific initial year TFP is thus obtained whilst taking into account parameter heterogeneity and base year values of inputs.

Fourth, for any particular year (excluding the initial year), TFP is calculated as:

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

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

3.2 Stochastic convergence tests

We apply LLC and KT tests to examine whether a stochastic convergence process was at play in terms of productivity amongst European regions over the covered interval. This is in line with a longstanding practice in applied macroeconomics (Fleissig and Strauss, 2001; Costantini and Lupi, 2005; Carrion-I-Silvestre and German Soto, 2007; Byrne, Fazio and Piacentino, 2009; Escobari, 2011; Chapsa, Athanasenas and Tabakis, 2018). The fundamental logic behind the tests is the following: if the difference between a given geographical unit's (country/region) macroeconomic series and the series' reference point is stationary, this would suggest an equilibrium relation and point towards a convergence process. The reference point could be the leading country/region, the overall sample average, or the average of a benchmark group. In the present analysis, we test i) whether regional TFPs converge to the entire sample's average, and ii) whether regional TFPs of member states that

joined the EU in and after 2004 converge to the average of the EU-12 regions. The EU-12 are the twelve founding member countries of the EU on the first of November 1993. They are considered to be the core EU countries¹⁰.

Under the first context (testing for convergence to the sample mean regional TFP), the series that we test is $\widetilde{\text{TFP}}_{it} = (\text{TFP}_{i,t} - \overline{\text{TFP}}_t)$, where $\text{TFP}_{i,t}$ is the TFP of region i at year t , and $\overline{\text{TFP}}_t$ is the cross-sectional TFP average in year t . Under the second context (testing for convergence to the EU-12 regional TFP average), the series that we test is $\widetilde{\text{TFP}}_{it} = (\text{TFP}_{i,t} - \overline{\text{TFP}}_{\text{EU12},t})$, where $\overline{\text{TFP}}_{\text{EU12},t}$ is the cross-sectional TFP average of the EU-12 regions in year t . Note that all measures of TFP are taken in natural logarithm.

The LLC test is applied on the following augmented Dickey Fuller regressions¹¹:

$$\Delta \widetilde{\text{TFP}}_{i,t} = \alpha_i + \phi \widetilde{\text{TFP}}_{i,t-1} + \sum_{j=1}^p \theta_{ij} \Delta \widetilde{\text{TFP}}_{i,t-j} + d_i t + \epsilon_{it} \quad (7)$$

where α_i is the region-specific mean, ϕ is the autoregressive parameter, t is a time trend, and ϵ_{it} is the error term. Lags of the dependent variable in equation (7) are added to purge serial correlation. In addition, the equation is estimated with a time trend, since plotting the series suggests the presence of a trend for most of the regions¹².

The null hypothesis is $\phi = 0$ (all panels are unit root processes), whereas the alternative is $\phi < 0$ (all panel time series are stationary processes). The rejection of the null is interpreted as evidence of convergence amongst regions.

The KT test has a number of interesting properties. In particular, it can be used in datasets with a short T as well as a large T dimension and allows for up to two endogenous breaks (Chen, Karavias and Tzavalis 2022). The null hypothesis is that all panel time series are unit root processes without breaks. The alternative hypothesis is that some or all panel time series are stationary processes with break(s) in the means. The visual investigation of the TFP series suggests that, for most of the regions, the breaks did not affect the trend but the intercept¹³. Consequently, we did not employ the KT model that allows for breaks in the intercepts and trends under the alternative hypothesis. We only consider breaks in the intercept, which corresponds to a change in the level of the TFP series. Rejecting the null is considered as evidence of convergence amongst all or some regions. The null hypothesis of nonstationarity can be written as:

$$H_0: \Delta \widetilde{\text{TFP}}_{it} = \Delta \widetilde{\text{TFP}}_{it-1} + u_{it} \quad (8)$$

In the case of one break in the means, the alternative hypothesis is given by:

¹⁰ The twelve countries that first formed the European Union are, in alphabetical order, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain and the United Kingdom.

¹¹ The LLC test is suitable for our dataset as it is recommended for panel datasets with moderate N dimension (between 10 and 250 panels) with 25 to 250 observations per panel (Levin, Lin and Chu, 2002).

¹² The series obtained by subtracting the cross-sectional EU TFP mean from regional TFPs are depicted in Appendix A. By and large, the rest of the series that are tested show the same pattern. To save space, we do not illustrate them; they are, however, available upon request.

¹³ The visual examination of the regional TFP series shows that, in most of the cases, the series are subject to structural breaks. Consequently, applying a PUR test that accommodates the latter is warranted.

$$H_1: \Delta \widetilde{\text{TFP}}_{it} = \varphi \Delta \widetilde{\text{TFP}}_{it-1} + (1 - \varphi)[a_{1i}I(t \leq b) + a_{2i}I(t > b)] + u_{it}, \quad (9)$$

where φ is the autoregressive parameter expected to be less than 1 under the alternative of stationarity; a_{1i} and a_{2i} respectively are the fixed effects before and after the break that occurs at date b ; $I(\cdot)$ is the indicator function; and u_{it} is the error term.

In the case of two breaks in the intercepts, the alternative hypothesis is the following:

$$H_1: \Delta \widetilde{\text{TFP}}_{it} = \varphi \Delta \widetilde{\text{TFP}}_{it-1} + (1 - \varphi)[a_{1i}I(t \leq b_1) + a_{2i}I(b_1 < t \leq b_2) + a_{3i}I(t > b_2)] + u_{it}, \quad (10)$$

where a_{1i} is the fixed effect before the first break (b_1); a_{2i} is the fixed effect between the first and the second break (b_2); and a_{3i} is the fixed effect after the second break.

3.3 Data, sources and pre-estimation analysis

Our data source is Cambridge Econometrics' European regional database¹⁴. Specifically, we use the following variables to estimate the production functions: total employment ("Temp2"), the gross domestic product at constant prices ("ROVGD2") and the gross fixed capital formation at constant prices ("GFCFeuro2"). The data is collected over the period 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, we consider a mix of NUTS-1 and 2 regional levels. The list of countries and regions is in Appendix B. To construct the capital stock, we employ the perpetual inventory method (see Appendix C).

Before implementing our empirical strategy, we investigate the cross-section dependence and time series properties of the variables used. Results, shown in Tables D.1, D.2 and D.3 in Appendix D, suggest that our variables exhibit cross-sectional dependence and are nonstationary processes. Table D.4 of Appendix D lays out the results of estimating equation (2).

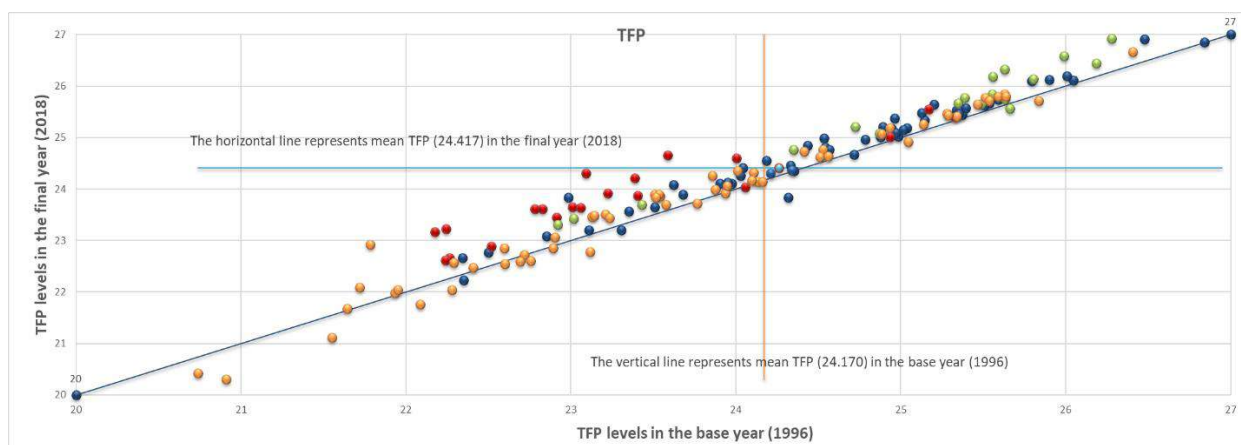
¹⁴ The database is available online on the following website: https://knowledge4policy.ec.europa.eu/territorial/ardec0-database_en

4 Findings

4.1 Descriptive analysis of regional TFP levels

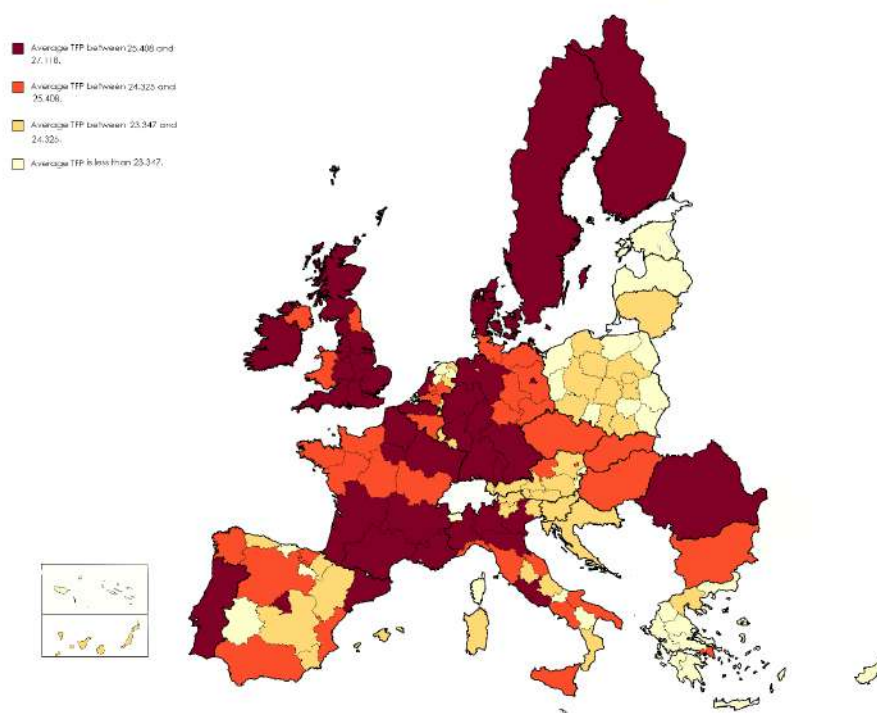
Figure 1 shows, for each of the regions, the TFP levels in the base year (1996) and the final year (2018) and depicts a 45-degree line to capture the evolution of TFP over the period. We notice an improvement in the TFP levels for most of the regions. In fact, few regions have a TFP level in the final year below that of the base year (dots below the 45-degree line). Most of these regions are in southern European countries (Greece, Italy and Spain). Figure 1 also shows the sample mean TFP value in the base year (the vertical orange line) and the final year (the horizontal blue line). Most of the regions in western and northern European countries have TFP levels in the base and final years above the sample averages (first, North-Eastern quadrant). Though the TFP levels for regions in eastern European countries improved, these regions still lag behind other regions. Their TFP levels in the base and final years are below the sample averages (third, South-Western quadrant). Regions in southern European countries are fairly distributed across the first and third quadrants.

Figure 1: Calculated TFP in the base (1996) and final year (2018) across regions in the EU



Note: regions in southern, western, northern and eastern European countries are represented respectively by the orange, blue, green and red dots.

Figure 2 shows the quartile average regional TFP values between 1996 and 2018. We notice that the regions with the highest average productivity levels are located mainly in western and northern Europe. Specifically, 30 of the 39 regions in the fourth quartile are located in Denmark, France, Germany, Ireland, Sweden and the UK; 8 regions are located in southern Europe (Italy, Portugal, and Spain), with Romania occupying the last position among the top performers. The mean TFP values in this group ranges between 25.4 (Romania) and 27.1 (North-Rhine Westphalia).

Figure 2: Quartile regional average TFP values over the period 1996-2018

Note: (i) the figure shows the spatial distribution of mean TFP values between 1996-2018 across regions; (ii) the two small boxes show the two outermost regions: Madeira and the Azores in Portugal (upper box), and the Canary Islands in Spain (lower box); (iii) Switzerland is left in white since it is not part of the EU.

On the other hand, the lowest mean TFP levels are the ones that prevailed in regions situated chiefly in southern and eastern Europe. Precisely, 33 of the 39 regions in the lowest quartile are located in Cyprus, Estonia, Italy, Latvia, Malta, Poland, Portugal and Spain. Only 6 regions in this group are in western and northern Europe. Productivity values in this group range between 20.5 (the Spanish autonomous city of Ceuta) and 23.3 (Cyprus). The geographical distribution across the two ends of the TFP spectrum is particularly informative: a productivity split seems to exist between northern and western Europe on one hand, and southern and eastern Europe on the other.

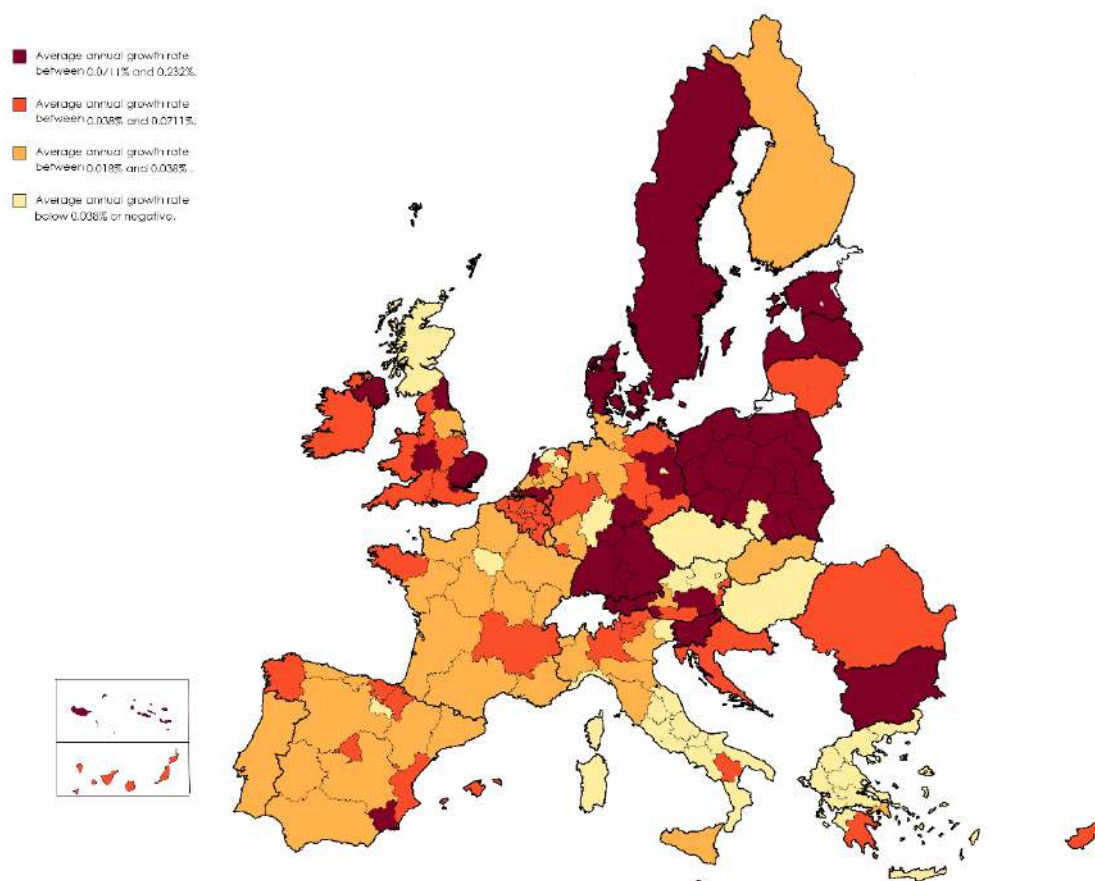
Figure 2 gives another interesting insight: there is evidence of productivity clusters in a number of locations. For instance, French regions with the highest average TFP over the period are grouped across i) south and central France (Auvergne-Rhône-Alpes, Nouvelle Aquitaine, Occitania, and Région Sud), and ii) north and northeast of France (Grand Est and Hauts de France). The UK provides another illustration of TFP clustering: the top performers are scattered across the south of England (London, Southeast and Southwest of England regions), central England (East Midlands and West Midlands) and eastern England (East of England, Southeast of England, and Northeast of England regions). Productivity agglomerations are also detectable in Germany, where the highest TFP values are registered in the former West Germany regions.

We can draw a third lesson from Figure 2: the existence of significant productivity disparities within some countries. This is notably the case in Italy, the Netherlands and Spain. In Italy, the best productivity regions are located in north and central Italy (Emilia-Romagna,

Lombardia, Piedmont, and Veneto), whilst the worst performers are typically situated in the south (Abruzzo, Basilicata, and Molise). Compared to Italy, the large regional productivity differences are more spatially diffused in the Netherlands and Spain.

Figure 3 plots the average annual growth rate of regional TFP between 1996 and 2018. We notice first that most of the regions which experienced the largest growth rates over the period are situated in eastern Europe (Bulgaria, Estonia, Latvia, Poland and Slovenia) and, to a lesser extent, in southern Europe (Portugal and Spain). Explicitly, nearly 51% of the regions of the top quartile are situated in eastern European countries (with 20 out of 39 regions); the share increases to almost 60% when we add regions located in southern Europe. Poland stands out in this respect; all the Polish regions (except one) are in the top quartile. Regions in the top quartile recorded an average annual growth rate ranging from 0.07% (Baden-Württemberg in Germany) to 0.23% (Masovian region in Poland). Since regions in this quartile are primarily located in eastern Europe, this points to a “catch-up” process, where regions in eastern Europe with initially lower productivities, catch up to regions in western and northern Europe with initially higher productivities.

Figure 3: Quartile regional average annual TFP growth rates over 1996-2018



Note: (i) the figure shows the spatial distribution of mean annual TFP growth rates over 1996-2018 across regions, classified into quartile 1 - quartile 4; (ii) notes (ii) and (iii) of Figure 2 apply.

The vast majority of regions with the lowest growth rates (including negative rates) are found in southern Europe, namely Greece, Italy and Spain. To be precise, of the 39 regions that constitute this group, 25 regions are located in these countries. Thus, the divide between southern Europe on one hand and northern and western Europe on the other is likely to remain entrenched. The mean annual TFP growth rate in this category ranges between -0.13% (the Spanish autonomous city of Ceuta) and 0.01% (Drenthe in the Netherlands). The least performing regions in Greece are islands (the Aegean islands, Crete, and the Ionian islands), the Macedonian regions (eastern Macedonia and Thrace, Central Macedonia, and western Macedonia), and neighbouring localities in the centre, east and west of Greece (Central Greece, Thessaly and Western Greece). Italian regions where TFP grew the least (and, in some cases, decreased over time) are situated in southern Italy (Abruzzo, Calabria, Campania, Molise and Puglia), in central and northern Italy (Friuli-Venezia Giulia, Lazio, Liguria, Marche, and Umbria) and Sardinia.

Moreover, western and northern European regions with the highest average TFP values over the sample period have experienced TFP growth rates in the middle of the distribution (i.e., in the second and third quartiles). Indeed, 55% of the regions grouped amongst the second and third quartiles are positioned in western and northern European countries. Overall, and in view of the goal of this paper, Figures 2 and 3 suggest a catch-up process, whereby regions with the lowest TFP values have been reducing the productivity gap with respect to the top European performers. This process seems to be mainly driven by regions located in the most recent EU member states: eastern European countries. The same tendency does not seem to hold in the case of many regions in southern Europe. In the next section, we formally test for the possibility of a convergence dynamic in TFP.

4.2 Regional TFP convergence

In this section, we present the results of the PUR tests discussed earlier, to investigate potential convergence between regional TFP series. In **Erreur! Argument de commutateur inconnu.**, we test for convergence of the regional TFP series in all EU member states (as of 2018) to the overall cross-sectional sample average. In the first three columns of the table, the PUR tests (LLC and KT) are conducted on the series \widehat{TFP}_{it} described in section 3.2. In the last three columns, the PUR tests are run on the demeaned \widehat{TFP}_{it} series: the difference between regional TFP (TFP_{it}) and the population-weighted TFP sample average. Demeaning the series is a common practice in PUR tests, to mitigate the impact of

cross-sectional dependence¹⁵. In the LLC test, the series are assumed to have a deterministic trend. The KT test assumes that the break does not affect the trend and that the error term is heteroskedastic¹⁶. The results from both the non-demeaned and demeaned series (Table 1) lead us to reject the null hypothesis of unit root (non-convergence). The endogenously calculated breaks in the KT test suggest that breaks in the data occur in 2008 (when one break is accommodated), and in 2008 and 2015 (when two breaks are accounted for). Hence, results from the LLC test support the hypothesis that all European regional TFPs are converging to the European TFP average. The KT tests suggest that at least some of the EU's regions converge in their TFP measures to the European average, whilst allowing for one or two breaks in the mean of the series. The first of the endogenously determined breaks in the KT test coincides with the financial crisis of 2007/8. The second break of 2015 coincides with the launch of the 2014-2020 round of the EU Cohesion Policy (programming period) and the end of the European sovereign debt crisis.

Table 1: PUR tests for all EU countries' regional TFP convergence to the EU regional average

	Tests applied on \widetilde{TFP}_{it}			Tests applied on demeaned \widetilde{TFP}_{it}		
	LLC	KT (with 1 break)	KT (with 2 breaks)	LLC*	KT* (with 1 break)	KT* (with 2 breaks)
N (panels)	155	155	155	155	155	155
T (periods)	23	23	23	23	23	23
p value	0.00	0.00	0.00	0.00	0.00	0.00
Breaks	-	2008	2008; 2015	-	2008	2008; 2015

Note: (i) LLC stands for the Levin, Lin and Chu (2002) test, KT stands for the Karavias and Tzavalis (2014) test; (ii) the tests are applied on the series obtained by differencing the EU TFP average from EU regions' TFP; (iii) the number of lags in the LLC test was chosen based on the Akaike information criterion.

We apply the same PUR tests to investigate whether the regional TFPs of the countries that joined the EU during and after the major expansion of 2004 converge to the EU-12 TFP average. The new countries that joined the EU in 2004 are labelled EU+10 (10 countries) and the new countries that joined the EU by 2013 are labelled EU+13 (13 countries)¹⁷. We subsequently run the same PUR tests on the series produced by taking the difference between the region's TFP and the EU-12 TFP average. The series are demeaned to account for cross-

¹⁵ The initial \widetilde{TFP}_{it} series was produced by taking the difference between the regional TFP series and the cross-sectional average of all TFP series. Hence, the nature of this calculated series does not allow for the standard demeaning procedure, whereby the cross-sectional average is subtracted from the series. To allow for demeaning, we construct the \widetilde{TFP}_{it} series as the difference between the region's TFP and the population-weighted average of the sample of all regions. Given that our sample includes NUTS-1 and NUTS-2 regions of different sizes, weighing the regional TFP by the population of the region seems an appropriate choice.

¹⁶ The regional TFP series depicted in Appendix A show that, for most of the regions, the break does not impact the trend. The other TFP series that are tested exhibit a similar pattern (available upon request).

¹⁷ The countries that joined the EU in 2004 are, by alphabetical order, Cyprus, Czechia, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia and Slovenia. Bulgaria and Romania joined the EU in 2007. The latest EU member is Croatia, which joined in 2013.

sectional dependence. The results are presented in **Erreur ! Argument de commutateur inconnu.** The results of the LLC test support the hypothesis that TFPs in the regions of the newest member states converge to the EU-12 TFP average. The results of the KT test support the hypothesis that at least some of the new members' regions converge in their TFP measures to the average EU-12 regional TFP, whilst allowing for breaks. Hence, EU expansion seems to be associated with converging productivity levels.

Table 2: PUR tests for new member states' regional TFP convergence to the EU-12 regional TFP average

	EU + 10			EU + 13		
	LLC	KT (with 1 break)	KT (with 2 breaks)	LLC	KT (with 1 break)	KT (with 2 breaks)
N (panels)	26	26	26	29	29	29
T (periods)	23	23	23	23	23	23
p value	0.00	0.00	0.00	0.00	0.00	0.00
Breaks	-	2008	2008; 2014	-	2008	2003; 2007

Note: (i) the first and the last notes of Table 1 apply; (ii) the tests are implemented on the series obtained by differencing the EU-12 TFP average from region's TFP.

Our overall findings suggest that TFP convergence is taking place across the EU regions to the EU regional average and across the regions of the new member states (from 2004) to the average TFP of the EU-12 regions. This confirms the results of TFP convergence across EU regions of several studies (Kijek and Matras Bolibok, 2020; Kijek, Kijek and Matras-Bolibok, 2023, Siller et al., 2021). Our analysis also adds to the evidence in the literature by confirming that at least some regional TFP series converge when endogenously determined structural breaks are considered. This is an important finding in view of the significance of the shocks that have affected the NUTS regions over the studied period.

We also test the robustness of these results to an alternative TFP series calculated using a depreciation rate of capital of 15% as opposed to 10% and virtually the same results come through minor differences, mainly related to the endogenously determined break dates. The robustness results are provided in Appendix E (Tables E.1 and E. 2).

5 Conclusion

We use data for a sample of 155 NUTS regions and derive regional TFP measurements over 1996-2018 in order to: (i) examine the extent and features of regional differences in terms of productivity; (ii) identify the leading regions, as well as the lagging ones, as to TFP levels; (iii) pinpoint regions that experienced a remarkable improvement in their productivity across the scrutinised period; and (iv) investigate whether a convergence in TFP was at play across NUTS regions, notwithstanding the shocks that impacted the latter over the studied interval.

Our empirical analysis leads to the following conclusions. First, our findings reveal significant disparities in productivity levels amongst the studied regions - sometimes within the same country. For the most part, the leading regions are located in the North and West of Europe, typically in the most developed members of the EU. On the other hand, the lowest levels of productivity are chiefly observed in regions situated in eastern and southern Europe. Thus, blatant imbalances in productivity across EU regions persist, with a clear TFP divide across eastern/southern Europe and northern/western Europe. Second, the vast majority of regions experienced an increase in TFP levels over the time span. Remarkably, the regions that registered the highest TFP annual average growth rate over the period are those located in eastern Europe. This hints at a catch-up process. Finally, there is evidence of a convergence process amongst regions in terms of productivity. Specifically, our results suggest that regional productivity values were converging to the EU average productivity. Furthermore, our findings also pinpoint to the convergence of the productivity in the regions of the new member states (that joined the EU in and after 2004) to the mean productivity of the EU-12 member states. Thus, differences in productivity levels amongst NUTS regions remained bounded over the covered period, notwithstanding the deepening of the integration process, along with the expansion of the EU. Interestingly, our findings indicate that the convergence dynamic did not break up, despite the identified structural breaks in the series.

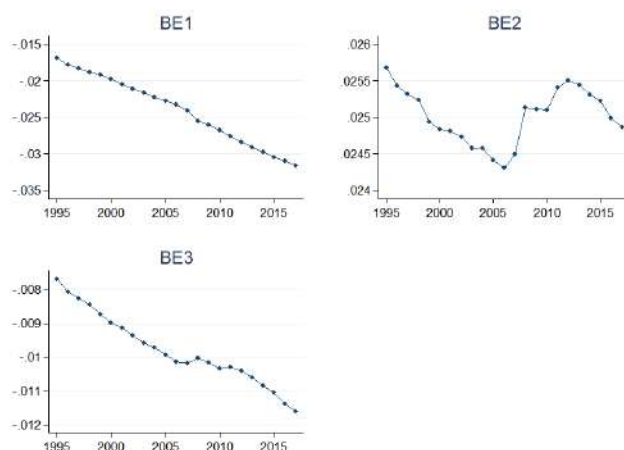
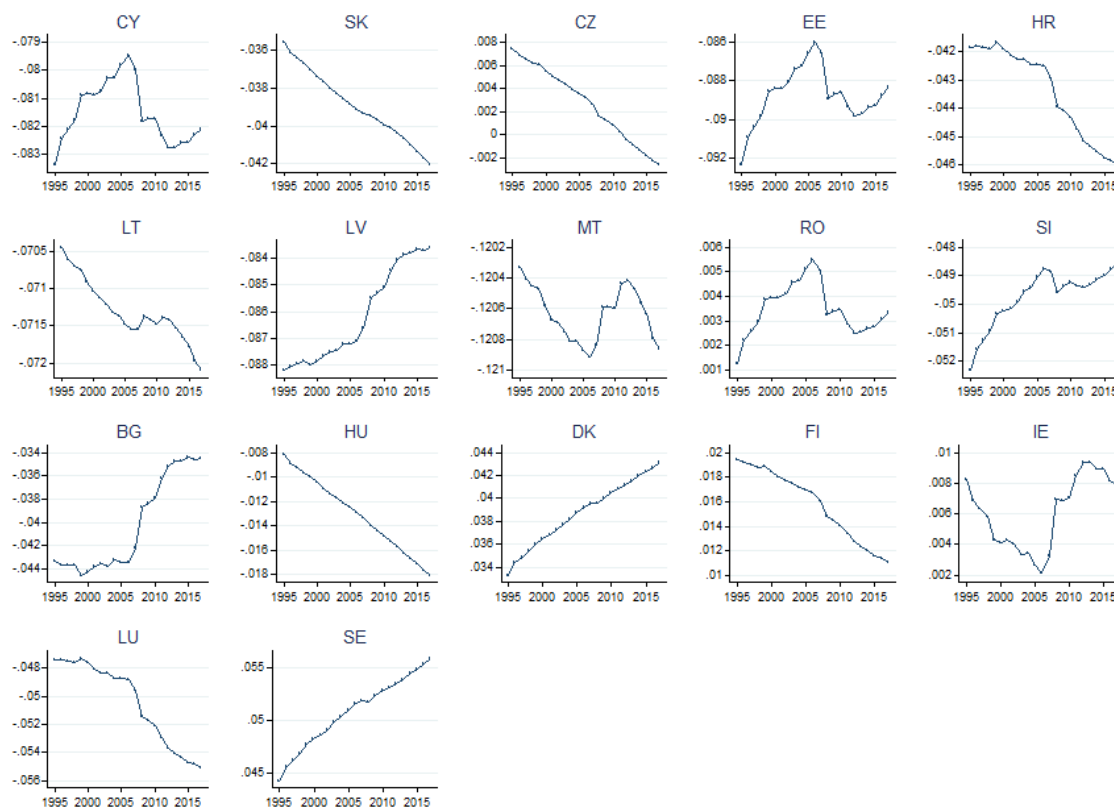
Our results suggest the following. Firstly, the identified convergence in productivity arguably reflects the conjunction of multi-faceted efforts deployed at the EU, country and regional levels to strengthen the cohesion of the Union and promote a catching-up process. Indeed, new member states managed to reduce the gap with respect to others in several areas that are critical to productivity gains, namely macroeconomic stability, sophistication of the financial markets and education. Furthermore, new member states deepened their economic relationships with the rest of the EU over the period examined, essentially through two vectors of technology transfer: international trade and FDI flows. Most likely, this has contributed to the convergence dynamic. Secondly, the productivity divide between leading and lagging regions/countries - notably those with feeble/negative TFP growth rates - suggests that the latter are still trailing in several factors that are conducive to productivity boosts. Chief amongst the latter factors are the institutional environment, the absorptive capacity and the competitiveness of the economy. Deficiencies in such areas are detrimental to productivity growth in lagging regions and countries, as they limit their capacity to adopt new technologies and to benefit from them. In view of the importance of the role played by TFP in driving growth and lessening economic disparities, measures that would stimulate productivity in regions/countries with the lowest TFP levels/growth would be warranted. Such measures could be delineated at the region, country, as well as the Union level. In this respect, the case of countries that experienced large regional TFP discrepancies is particularly

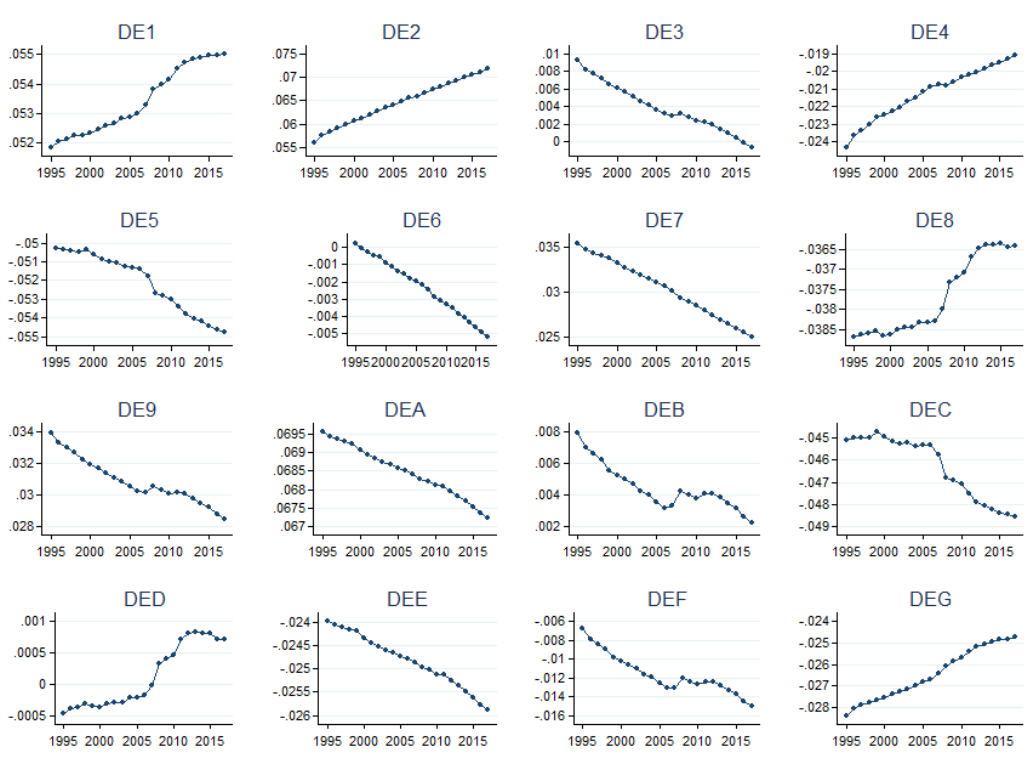
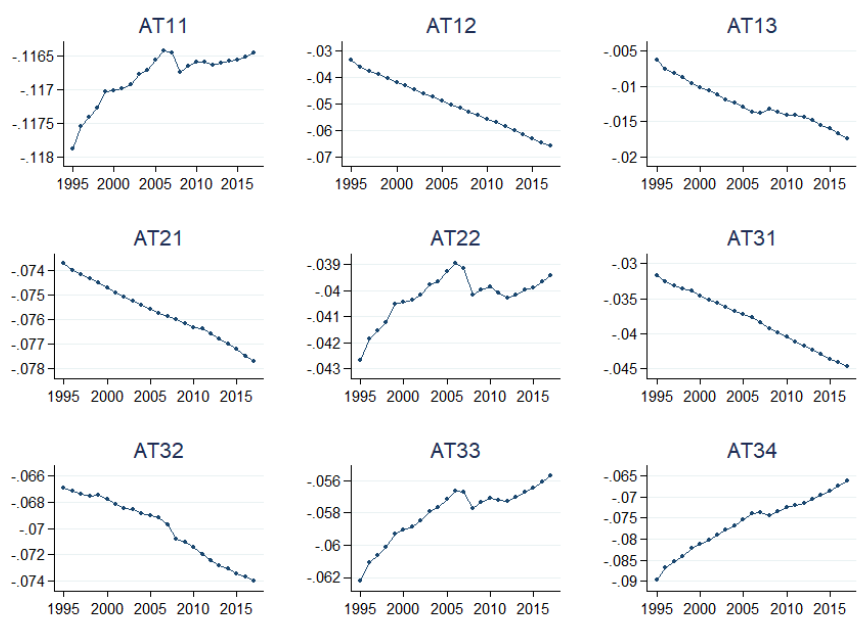
important. Indeed, there is a need to coordinate regional, national and Union endeavours, to address the challenges faced by the lagging regions, in order to immediately foster a double convergence process - at the national level, as well as the EU level.

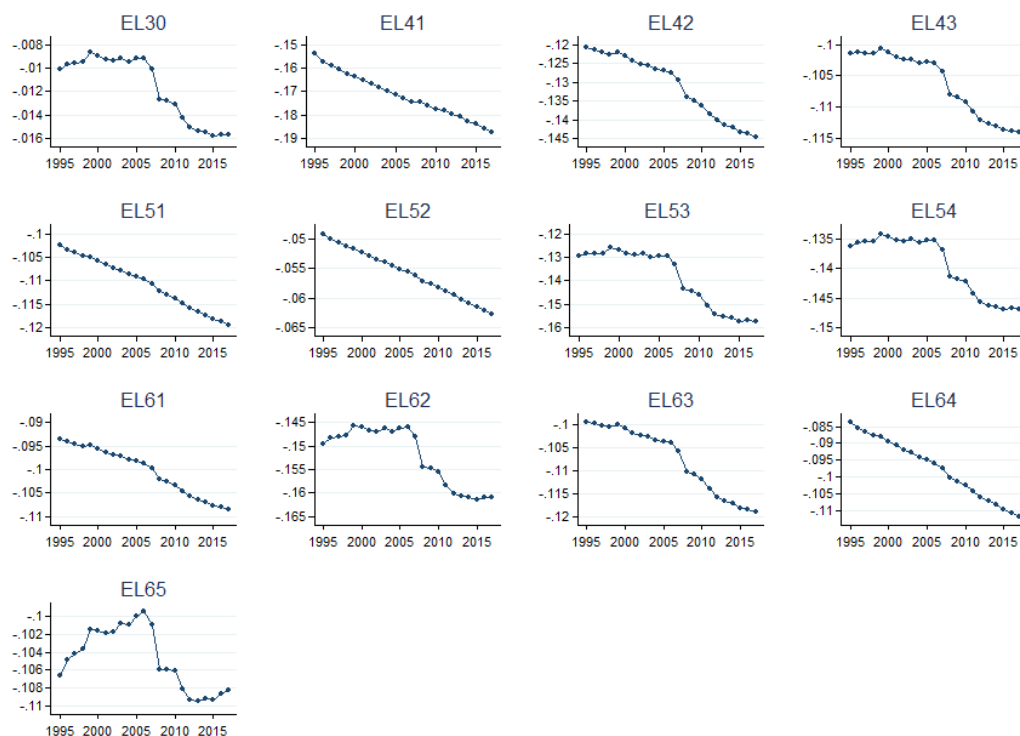
The present analysis can be extended in at least two directions. Firstly, the last year covered in our empirical analysis is 2018 for data availability reasons¹⁸. Once more recent data becomes available, it would be possible to further stretch the investigation in time. This will allow researchers to examine the likely effect that substantial shocks, which impacted our sample in the post-2018 period (notably the Covid-19 pandemic), had on regional productivity disparities and the convergence process. Secondly, our research identifies the regions that are lagging in TFP. Another possible extension of the present research would investigate the factors that can explain the poor performance of the trailing regions.

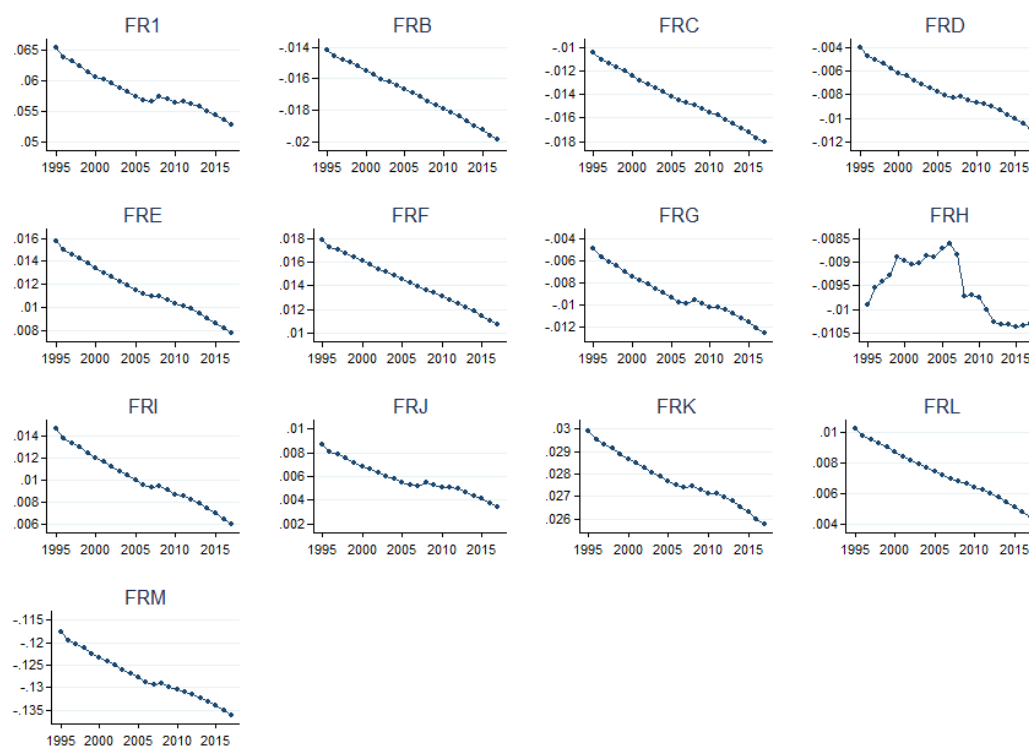
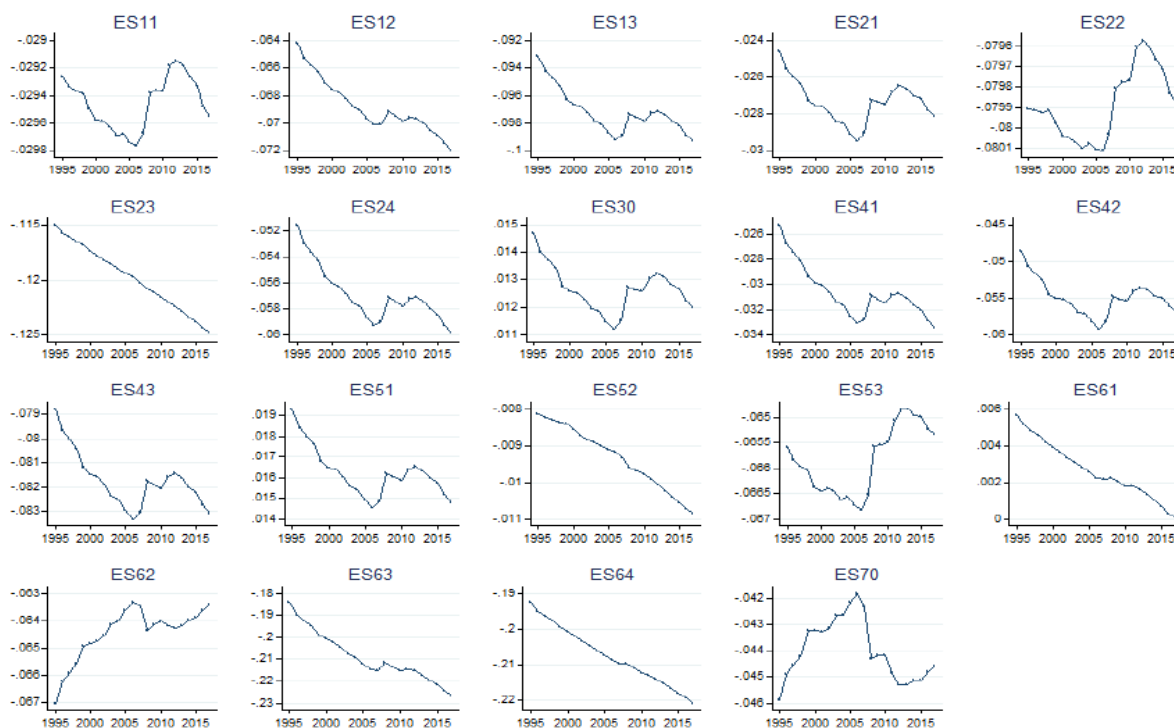
¹⁸ Data used to estimate the production functions is available up to 2022. However, the 2019-2022 figures are predicted, based on the 2015-2018 trend. Given the significant effect of the Covid-19 pandemic, it is very likely that the forecast is off the mark; thus, we did not use the 2019-2022 projected values.

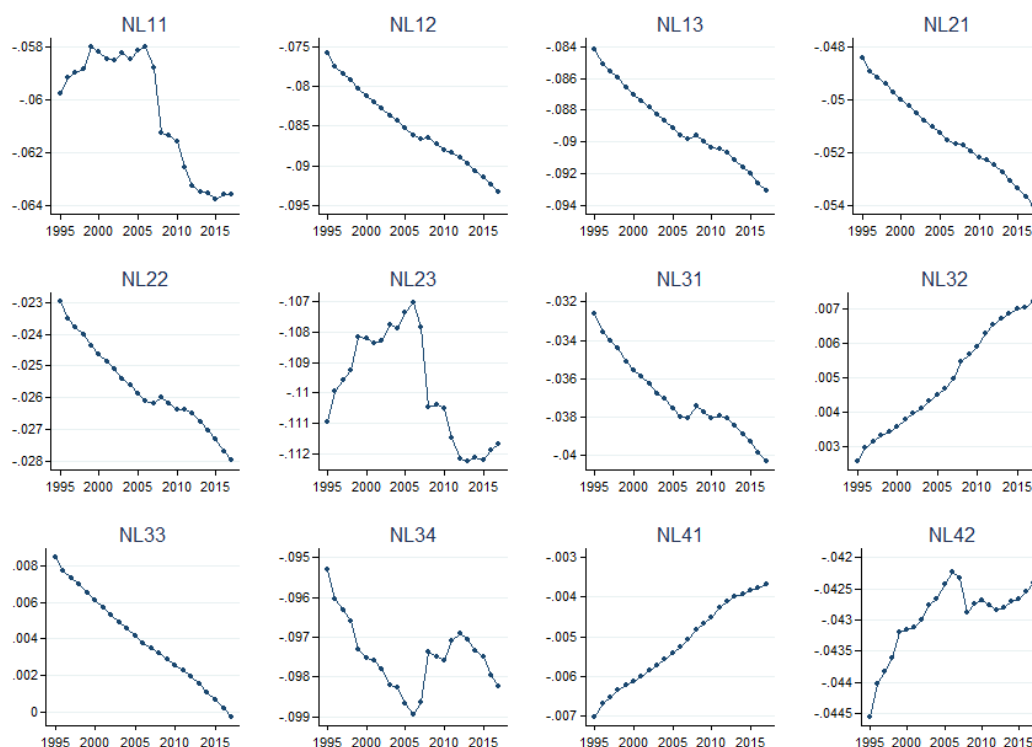
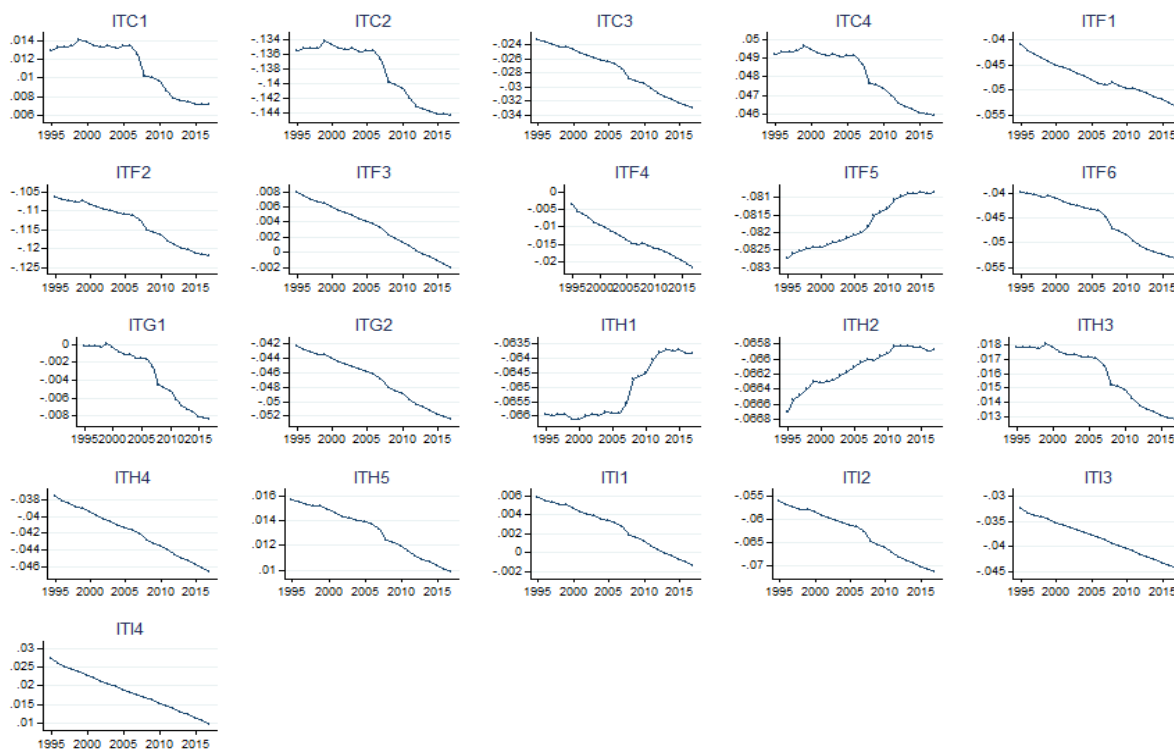
6 Appendix A: Plotting the \widehat{TFP}_{it} series (the difference between the regional TFP and the EU mean TFP) for all regions

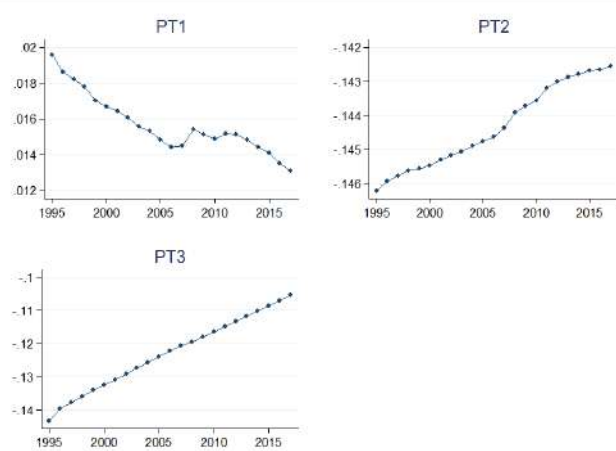
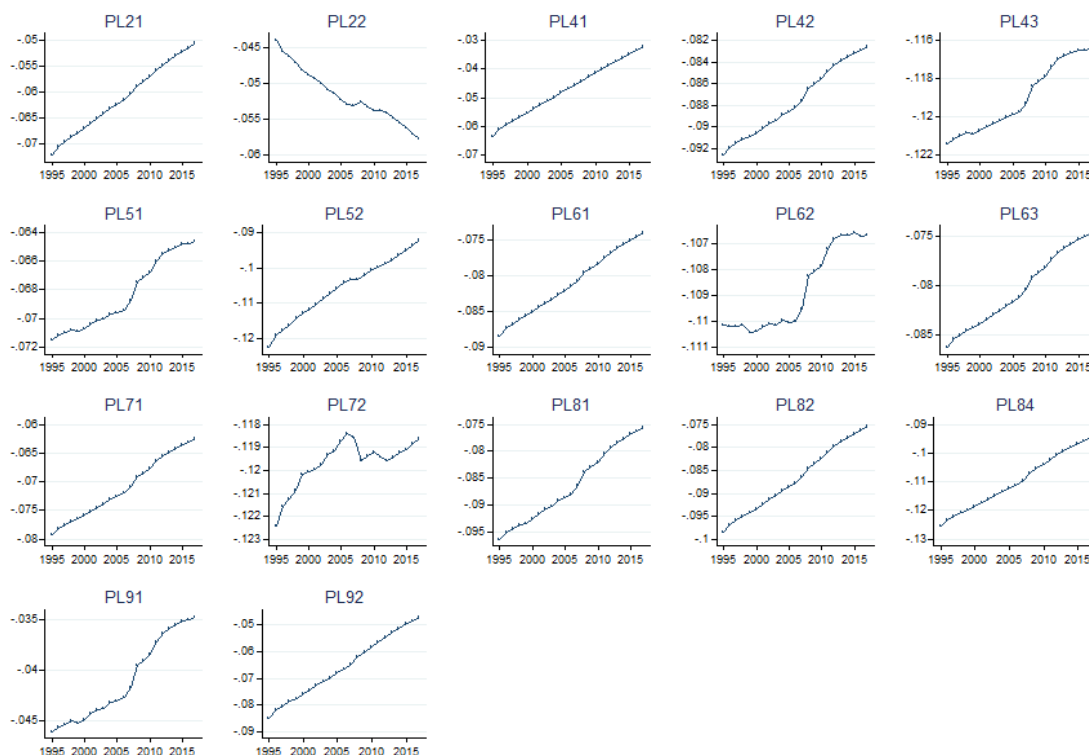


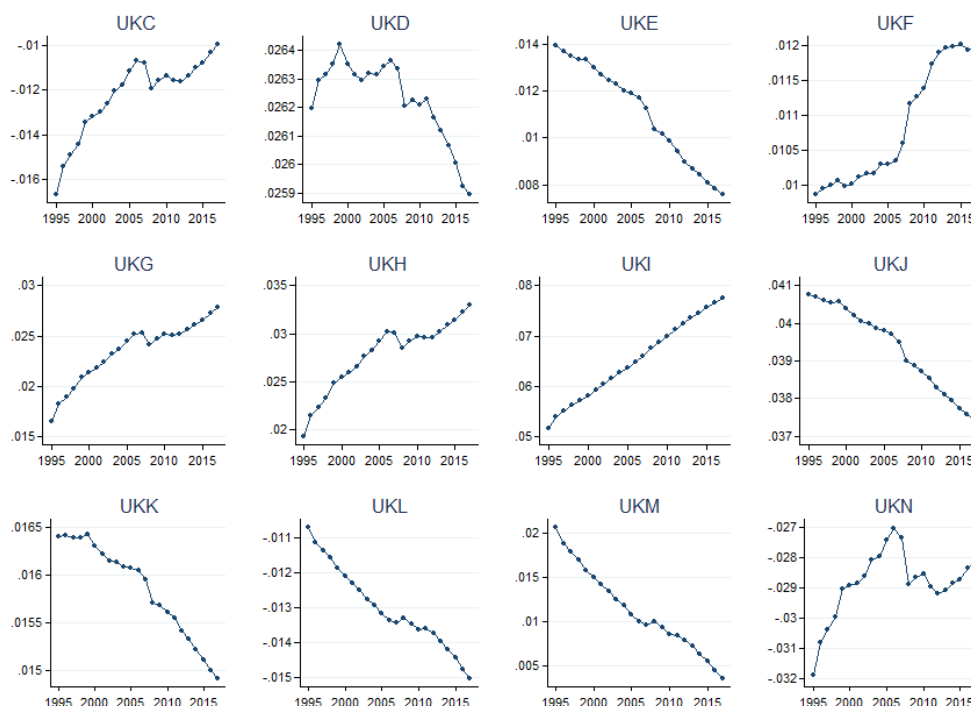












Note: the figure shows the series across 155 NUTS regions. For details about the regions, regions codes and countries covered, refer to Appendix B.

7 Appendix B: Sample of countries, NUTS regions, and NUTS levels used

Country	Country code	Region code	id	NUTS level	Name of the region
Austria	AT	AT11	ATAT11	2	AT11: Burgenland
Austria	AT	AT12	ATAT12	2	AT12: Lower Austria
Austria	AT	AT13	ATAT13	2	AT13: Vienna
Austria	AT	AT21	ATAT21	2	AT21: Carinthia
Austria	AT	AT22	ATAT22	2	AT22: Styria
Austria	AT	AT31	ATAT31	2	AT31: Upper Austria
Austria	AT	AT32	ATAT32	2	AT32: Salzburg
Austria	AT	AT33	ATAT33	2	AT33: Tyrol
Austria	AT	AT34	ATAT34	2	AT34: Vorarlberg
Belgium	BE	BE1	BEBE1	1	BE1 Brussels Capital Region
Belgium	BE	BE2	BEBE2	1	BE2 Flemish Region
Belgium	BE	BE3	BEBE3	1	BE3 Wallonia
Bulgaria	BG	BG	BGBG3	0	BGR: Bulgaria

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Cyprus	CY	CY0	CYCY0	0-1	Cyprus
Czechia	CZ	CZ	CZCZ	0-1	CZE: Czech Republic
Germany	DE	DE1	DEDE1	1	DE1: Baden-Württemberg
Germany	DE	DE2	DEDE2	1	DE2: Bavaria
Germany	DE	DE3	DEDE3	1	DE3: Berlin
Germany	DE	DE4	DEDE4	1	DE4: Brandenburg
Germany	DE	DE5	DEDE5	1	DE5: Bremen
Germany	DE	DE6	DEDE6	1	DE6: Hamburg
Germany	DE	DE7	DEDE7	1	DE7: Hesse
Germany	DE	DE8	DEDE8	1	DE8: Mecklenburg-Vorpommern
Germany	DE	DE9	DEDE9	1	DE9: Lower Saxony
Germany	DE	DEA	DEDEA	1	DEA: North Rhine-Westphalia
Germany	DE	DEB	DEDEB	1	DEB: Rhineland-Palatinate
Germany	DE	DEC	DEDEC	1	DEC: Saarland
Germany	DE	DED	DEDED	1	DED: Saxony
Germany	DE	DEE	DEDEE	1	DEE: Saxony-Anhalt
Germany	DE	DEF	DEDEF	1	DEF: Schleswig-Holstein
Germany	DE	DEG	DEDEG	1	DEG: Thuringia
Denmark	DK	DK0	DKDK0	0-1	DNK: Denmark
Estonia	EE	EE0	EEEE0	1	EST: Estonia
Greece	EL	EL30	ELEL30	2	EL30: Attica
Greece	EL	EL41	ELEL41	2	EL41: North Aegean
Greece	EL	EL42	ELEL42	2	EL42: South Aegean
Greece	EL	EL43	ELEL43	2	EL43: Crete
Greece	EL	EL51	ELEL51	2	EL51: Eastern Macedonia, Thrace
Greece	EL	EL52	ELEL52	2	EL52: Central Macedonia
Greece	EL	EL53	ELEL53	2	EL53: Western Macedonia
Greece	EL	EL54	ELEL54	2	EL54: Epirus
Greece	EL	EL61	ELEL61	2	EL61: Thessaly
Greece	EL	EL62	ELEL62	2	EL62: Ionian Islands
Greece	EL	EL63	ELEL63	2	EL63: Western Greece
Greece	EL	EL64	ELEL64	2	EL64: Central Greece
Greece	EL	EL65	ELEL65	2	EL65: Peloponnese
Spain	ES	ES11	ESES11	2	ES11: Galicia
Spain	ES	ES12	ESES12	2	ES12: Asturias
Spain	ES	ES13	ESES13	2	ES13: Cantabria
Spain	ES	ES21	ESES21	2	ES21: Basque Country
Spain	ES	ES22	ESES22	2	ES22: Navarra
Spain	ES	ES23	ESES23	2	ES23: La Rioja
Spain	ES	ES24	ESES24	2	ES24: Aragon
Spain	ES	ES30	ESES30	2	ES30: Madrid
Spain	ES	ES41	ESES41	2	ES41: Castile and León

Spain	ES	ES42	ESES42	2	ES42: Castile-La Mancha
Spain	ES	ES43	ESES43	2	ES43: Extremadura
Spain	ES	ES51	ESES51	2	ES51: Catalonia
Spain	ES	ES52	ESES52	2	ES52: Valencia
Spain	ES	ES53	ESES53	2	ES53: Balearic Islands
Spain	ES	ES61	ESES61	2	ES61: Andalusia
Spain	ES	ES62	ESES62	2	ES62: Murcia
Spain	ES	ES63	ESES63	2	ES63: Ceuta
Spain	ES	ES64	ESES64	2	ES64: Melilla
Spain	ES	ES70	ESES70	2	ES70: Canary Islands
Finland	FI	FI1	FIFI1	0-1	Finland
France	FR	FR1	FRFR1	1	FR1: Île-de-France
France	FR	FRB	FRFRB	1	FRB: Centre - Val de Loire
France	FR	FRC	FRFRC	1	FRC: Bourgogne-Franche-Comté
France	FR	FRD	FRFRD	1	FRD: Normandy
France	FR	FRE	FRFRE	1	FRE: Hauts-de-France
France	FR	FRF	FRFRF	1	FRF: Grand Est
France	FR	FRG	FRFRG	1	FRG: Pays de la Loire
France	FR	FRH	FRFRH	1	FRH: Brittany
France	FR	FRI	FRFRI	1	FRI: Nouvelle-Aquitaine
France	FR	FRJ	FRFRJ	1	FRJ: Occitanie
France	FR	FRK	FRFRK	1	FRK: Auvergne-Rhône-Alpes
France	FR	FRL	FRFRL	1	FRL: Provence-Alpes-Côte d'Azur
France	FR	FRM	FRFRM	1	FRM: Corsica
Croatia	HR	HR	HRHR	0-1	Croatia
Hungary	HU	HU	HUHU1	0	HUN: Hungary
Ireland	IE	IE0	IEIE0	1	IRL: Ireland
Italy	IT	ITC1	ITITC1	2	ITC1: Piedmont
Italy	IT	ITC2	ITITC2	2	ITC2: Aosta Valley
Italy	IT	ITC3	ITITC3	2	ITC3: Liguria
Italy	IT	ITC4	ITITC4	2	ITC4: Lombardy
Italy	IT	ITF1	ITITF1	2	ITF1: Abruzzo
Italy	IT	ITF2	ITITF2	2	ITF2: Molise
Italy	IT	ITF3	ITITF3	2	ITF3: Campania
Italy	IT	ITF4	ITITF4	2	ITF4: Apulia
Italy	IT	ITF5	ITITF5	2	ITF5: Basilicata
Italy	IT	ITF6	ITITF6	2	ITF6: Calabria
Italy	IT	ITG1	ITITG1	2	ITG1: Sicily
Italy	IT	ITG2	ITITG2	2	ITG2: Sardinia
Italy	IT	ITH1	ITITH1	2	ITH1: Province of Bolzano-Bozen
Italy	IT	ITH2	ITITH2	2	ITH2: Province of Trento
Italy	IT	ITH3	ITITH3	2	ITH3: Veneto

Italy	IT	ITH4	ITITH4	2	ITH4: Friuli-Venezia Giulia
Italy	IT	ITH5	ITITH5	2	ITH5: Emilia-Romagna
Italy	IT	ITI1	ITITI1	2	ITI1: Tuscany
Italy	IT	ITI2	ITITI2	2	ITI2: Umbria
Italy	IT	ITI3	ITITI3	2	ITI3: Marche
Italy	IT	ITI4	ITITI4	2	ITI4: Lazio
Lithuania	LT	LT	LTLT	0-1	LTU: Lithuania
Luxembourg	LU	LU0	LULU0	1	LUX: Luxembourg
Latvia	LV	LV0	LVLV0	1	LVA: Latvia
Malta	MT	MT0	MTMT0	1	MLT: Malta
Netherlands	NL	NL11	NLNL11	2	NL11: Groningen
Netherlands	NL	NL12	NLNL12	2	NL12: Friesland
Netherlands	NL	NL13	NLNL13	2	NL13: Drenthe
Netherlands	NL	NL21	NLNL21	2	NL21: Overijssel
Netherlands	NL	NL22	NLNL22	2	NL22: Gelderland
Netherlands	NL	NL23	NLNL23	2	NL23: Flevoland
Netherlands	NL	NL31	NLNL31	2	NL31: Utrecht
Netherlands	NL	NL32	NLNL32	2	NL32: North Holland
Netherlands	NL	NL33	NLNL33	2	NL33: South Holland
Netherlands	NL	NL34	NLNL34	2	NL34: Zeeland
Netherlands	NL	NL41	NLNL41	2	NL41: North Brabant
Netherlands	NL	NL42	NLNL42	2	NL42: Limburg
Poland	PL	PL21	PLPL21	2	PL21: Lesser Poland
Poland	PL	PL22	PLPL22	2	PL22: Silesia
Poland	PL	PL41	PLPL41	2	PL41: Greater Poland
Poland	PL	PL42	PLPL42	2	PL42: West Pomerania
Poland	PL	PL43	PLPL43	2	PL43: Lubusz
Poland	PL	PL51	PLPL51	2	PL51: Lower Silesia
Poland	PL	PL52	PLPL52	2	PL52: Opole region
Poland	PL	PL61	PLPL61	2	PL61: Kuyavian-Pomerania
Poland	PL	PL62	PLPL62	2	PL62: Warmian-Masuria
Poland	PL	PL63	PLPL63	2	PL63: Pomerania
Poland	PL	PL71	PLPL71	2	PL71: Lodzkie
Poland	PL	PL72	PLPL72	2	PL72: Swietokrzyskie
Poland	PL	PL81	PLPL81	2	PL81: Lublin Province
Poland	PL	PL82	PLPL82	2	PL82: Podkarpacia
Poland	PL	PL84	PLPL84	2	PL84: Podlaskie
Poland	PL	PL91	PLPL91	2	PL91: Warsaw's capital city
Poland	PL	PL92	PLPL92	2	PL92: Mazowiecki region
Portugal	PT	PT1	PTPT1	1	Portugal
Portugal	PT	PT2	PTPT2	1	PT20: Autonomous Region of the Azores

Portugal	PT	PT3	PTPT3	1	PT30: Autonomous Region of Madeira
Romania	RO	RO	RORO	0	ROU: Romania
Sweden	SE	SE	SESE	0	SWE: Sweden
Slovenia	SI	SI	SISI	1	SVN: Slovenia
Slovakia	SK	SK	SKSK	0-1	SVK: Slovak Republic
United Kingdom	UK	UKC	UKUKC	1	UKC: North East England
United Kingdom	UK	UKD	UKUKD	1	UKD: North West England
United Kingdom	UK	UKE	UKUKE	1	UKE: Yorkshire and The Humber
United Kingdom	UK	UKF	UKUKF	1	UKF: East Midlands
United Kingdom	UK	UKG	UKUKG	1	UKG: West Midlands
United Kingdom	UK	UKH	UKUKH	1	UKH: East of England
United Kingdom	UK	UKI	UKUKI	1	UKI: Greater London
United Kingdom	UK	UKJ	UKUKJ	1	UKJ: South East England
United Kingdom	UK	UKK	UKUKK	1	UKK: South West England
United Kingdom	UK	UKL	UKUKL	1	UKL: Wales
United Kingdom	UK	UKM	UKUKM	1	UKM: Scotland
United Kingdom	UK	UKN	UKUKN	1	UKN: Northern Ireland

8 Appendix C: Note on the data used and capital stock series

The Cambridge Econometrics' European regional database is available over the period 1980-2022. However, the data for the period 2019-2022 is predicted, based on the 2015-2018 trend. Given the heavy repercussions of the shock embodied by the outbreak of the Covid-19 virus, it is highly likely that the 2019-2022 forecast is off the mark. Thus, we used the data spanning 1995-2018 to estimate regional production functions. Since the first differencing process of stage 1 of the AMG estimation shortens the period by one year, the ensuing TFP series cover the 1996-2018 span.

To estimate the production functions, we needed to construct regional capital stock series from the gross fixed capital formation (GFCF) series. To do so, we employed the perpetual inventory method, based on the next expression:

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

Where the capital stock of period t (k_t) is equal to the previous period's capital stock (k_{t-1}), from which the capital depreciation is subtracted and to which the GFCF of period t is added (I_t). The initial year capital stock is typically a function of initial year GFCF (I_0) and computed as follows:

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

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 is convenient, since it 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 adopted a main depreciation rate of 10% (we also used a 15% depreciation rate as a robustness check) and employed the average annual growth rate of GFCF over the first 7 years of available observations as the growth rate of investment.

9 Appendix D: Data analysis and AMG regression results

Table D.1: Pesaran (2015) cross-section dependence test

	y	L	K
CD test	535.19	535.19	535.17
p -value	0.00	0.00	0.00

Note: (i) the null hypothesis is weak cross-section dependence, the CD test statistic is normally distributed under the null; (ii) y , l , and k are in logs.

Table D.2: Pesaran (2007) panel unit root (CIPS) test, variables in level

Y			l			k		
lags	Z [t-bar]	p -value	lags	Z [t-bar]	p -value	lags	Z [t-bar]	p -value
0	4.97	1.00	0	7.46	1.00	0	16.38	1.00
1	1.11	0.86	1	2.27	0.98	1	2.23	0.98
2	-0.17	0.43	2	4.45	1.00	2	3.15	0.99
3	1.05	0.85	3	5.64	1.00	3	5.77	1.00

Note: (i) the test is based on country-specific augmented Dickey Fuller regressions, robust to cross-section correlation (augmentation with lags, as mentioned), the null hypothesis is nonstationarity across all panels; (ii) y , l , and k are in logs.

Table D.3: Pesaran (2007) panel unit root (CIPS) test, variables in first difference

Δy			Δl			Δk		
lags	Z [t-bar]	p -value	lags	Z [t-bar]	p -value	lags	Z [t-bar]	p -value
0	-25.60	0.00	0	-19.54	0.00	0	-7.22	0.00
1	-15.71	0.00	1	-11.61	0.00	1	-7.18	0.00

2	-11.14	0.00	2	-5.74	0.00	2	-6.62	0.00
3	-10.66	0.00	3	-1.27	0.10	3	-4.61	0.00

Note: the note of the previous table applies.

Table D.4: 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 ($H_0: \frac{1}{N} \sum_i \beta_i = 0$); (iii) *** denotes significance at 1%; (iv) "RMSE" refers to the root mean square error; (v) l and k are in logs.

10 Appendix E: Convergence tests (robustness checks)

Table E.1: PUR tests for all EU countries' regional TFP convergence to the EU regional average

	LLC	KT (with 1 break)	KT (with 2 breaks)	LLC*	KT* (with 1 break)	KT* (with 2 breaks)
N (panels)	155	155	155	155	155	155
T (periods)	23	23	23	23	23	23
p value	0.00	0.00	0.00	0.00	0.00	0.00
Breaks	-	2008	2008; 2015	-	2008	2008; 2015

Note: (i) LLC stands for the Levin et al. (2002) test; KT stands for the Karavias and Tzavalis (2014) test; (ii) the tests are applied on the series obtained by differencing the EU TFP average from EU regions' TFP; (iii) starred tests refer to the case where they are applied on demeaned series, to account for cross-sectional dependence.

Table E.2: PUR tests for new member states' regional TFP convergence to the EU-12 regional TFP average

	EU + 10			EU + 13		
	LLC	KT (with 1 break)	KT (with 2 breaks)	LLC	KT (with 1 break)	KT (with 2 breaks)
N (panels)	26	26	26	29	29	29
T (periods)	23	23	23	23	23	23
p value	0.00	0.00	0.00	0.00	0.00	0.00
Breaks	-	2007	2002; 2007	-	2008	2004; 2008

Note: (i) the first note of Table 1 applies; (ii) the tests are implemented on the series obtained by differencing the EU-12 TFP average from region's TFP; (iii) the tested series are demeaned to account for cross-sectional dependence.

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