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TFP convergence across European regions

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Abstract

This paper proposes a fixed-effect panel methodology that enables us to simultaneously take into account both TFP convergence and the traditional neoclassical-type of convergence. We analyse a sample of 199 European regions between 1985 and 2006 and find the absence of an overall process of TFP convergence as we observe that TFP dispersion is virtually constant across the two sub-periods. However, the absence of a strong process of TFP convergence hides interesting and complex dynamic patterns across regions as we observe significant changes in countries ranking. These results suggest that while obtaining fast growth in TFP is not simple, it appears to be a key factor in achieving fast per capita value added growth. Our results are robust to the use of different estimation procedures such as simple LSDV, Kiviet-corrected LSDV, and GMM à la Arellano and Bond.

Keywords: TFP, technology diffusion, panel data.

JEL code: O47, O33, C23.

Preliminary and incomplete – not for quotation

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1. Introduction

A large body of empirical evidence on cross-country economic growth reveals the coexistence of both the presence of weak (or the absence of) processes of absolute convergence and of large TFP differentials (Pritchett, 1997; Durlauf *et al.*, 2005; Grier *et al.*, 2007). In other words, even if large differences in estimated TFP levels should imply the presence of flows of technology from advanced to less developed areas we observe that these diffusion processes are far from easy and instantaneous.

Evidence on large differences in the rate of technology adoption across large samples of countries are usually explained by differences in human capital stocks, as firstly suggested by Nelson and Phelps (1966), and/or by quality institutions heterogeneity, (Hall and Jones, 1999; Acemoglu *et al.*, 2001 and 2006, Comin and Hobijt, 2009), and/or by the existence of monopoly rights of various forms that create a barrier to technology adoption, as in Parente and Prescott (1999). These factors are usually considered as the major However, more puzzling is the evidence that slow processes of technology adoption are observed even across similar leading countries of the world economy.¹

As maintained more than ten years ago by Bernard and Jones (1996), in order to investigate convergence dynamics across economies we need to focus on a direct analysis of the evolution of TFP levels over time. However, while the idea may sound quite simple, giving it an operational content is not an easy task. That is, estimating TFP levels and identifying the role of technology diffusion within income convergence is not simple. What is usually needed for TFP is a measure of output differences which is not explained by different input choices and occurs, instead, through marginal product increases. An array of methodologies is available, none of which has emerged so far as a recognized standard (Del Gatto *et al.*, 2010).

In this paper we use data on VA per capita of 199 EU regions over the period 1985-2006 and test for the presence of TFP heterogeneity and TFP div/convergence. Unlike previous papers of TFP across EU regions (see in particular Dettori *et al.*, 2008²), our choice builds on Islam (2003), in which the presence of TFP heterogeneity in cross-country convergence analysis is tested by using a fixed-effects panel estimator in a standard convergence equation framework. It has been shown that this framework can be used to examine cases in which TFP differences in levels are not constants and, therefore, it allows us to estimate TFP at different points in time and test for the presence of

¹ See, for example, Comin and Hobijt (2004) who explore the adoption of 20 technologies across 23 leading countries over more than two centuries. The high variance in the rates of adoption is confirmed by Comin *et al.* (2008), who study the diffusion of 10 technologies across 185 countries.

² Dettori *et al.* (2008) derive a regression based measure of regional TFP without imposing a priori restrictions on the inputs elasticities of a Cobb-Douglas function. Interestingly this function does not include only traditional inputs but also a measure of spatial interdependences across regions.

TFP convergence.³ The main feature of this framework is that TFP levels are estimated by means of growth regressions in which the contribution of factor accumulation – namely, capital deepening – to income convergence is taken into account. By doing this, we limit the risk of overstating the role of TFP dynamics within that process.

The robustness of our results is assessed by comparing the estimates obtained by using different estimators, namely, OLS, a Least Square with Dummy Variable (LSDV) estimator, a biased-corrected LSDV estimator (Kiviet, 1995) and a GMM (Arellano-Bond, 1991) estimator. We use a procedure suggested by Bond *et al.* (2001) and Monte Carlo results to select plausible estimates.

We use data on per capita Value Added of 199 EU regions over the period 1985-2006. It is worth underlining that this time span is longer than those used by most of the other available papers on TFP dynamics across EU regions⁴ and includes the decade characterized by the IT revolution, a phenomenon known to be the source of a significant asymmetric shock on productivity levels, with the more developed economies as the major beneficiaries.⁵

Our results confirm that cross-regions gaps in TFP levels are significant, that they are persistent, and that they are an important component of VA per capita dynamics. In particular, we do not find support to the hypothesis that a process of global TFP convergence has been present and the same phenomenon characterises cross-regions VA per capita. The persistence of TFP differentials is strongly confirmed by the analysis of the shape of the whole cross-region distribution, which remains almost identical across periods. The link between TFP and VA cross-region performances in time is further supported by the strong correlation existing between changes in TFP and VA rankings. At the same time this does not imply the absence of any cross-regions dynamics in TFP. Conversely, during the time span examined we observe the presence of strong intra-distribution processes with significant changes in regional ranking.

The paper is organized as follows. In section 2 we describe our chosen methodology to estimate TFP levels at different point in time, while in section 3 we discuss how to select the estimator that suits our case better and presents our evidence on degrees of cross-region TFP heterogeneity. Section 4 shows how much TFP convergence can be detected in our dataset and section 5 tests if our estimated TFP growth rates are positively correlated with the observed human capital endowments. Finally, section 6 shows some evidence on the specific role different levels of

³ See Di Liberto *et al.* (2008) for more details. More generally, this methodology offers various advantages with respect to existing alternatives. In particular, it neither calls for the imposition of too many assumptions nor it requires the use of large datasets. These problems may be present, for instance, with techniques such as growth/level accounting and DEA.

⁴ One exception is Dettori *et al.* (2008) who use the same geographical and temporal sample of this paper.

⁵ See Jorgenson (2005) and Inklaar *et al.* (2005) on cross-country analysis.

education play on TFP growth. Conclusions are in section 7.

2. A Panel Data approach to estimate TFP convergence

Our aim is to investigate cross-region TFP heterogeneity and convergence by using an appropriate fixed-effect panel estimator. Islam (1995) was among the first to suggest this econometric solution to the problem of controlling for TFP heterogeneity in convergence analysis.⁶ In particular, he extended the standard Mankiw *et al.* (1992) structural approach by allowing TFP levels to vary across individual economies, together with saving rates and population growth rates. Unlike in the Mankiw *et al.* (1992) approach, Islam (1995) introduced the idea that the unobservable differences in TFP are correlated with other regressors, and uses suitable panel techniques to estimate:

$$y_{it} = \beta y_{it-\tau} + \sum_{j=1}^2 \gamma_j x_{j,it} + \eta_t + \mu_i + v_{it} \quad j=1,2 \quad (1)$$

where the dependent variable is the logarithm of *per capita* VA (measured in terms of population working age), v_{it} is the transitory term that varies across countries. The remaining terms are:

$$x_{1,it} = \ln(s_{it}) \quad (2)$$

$$x_{2,it} = \ln(n_{it} + g + \delta) \quad (3)$$

$$\gamma_1 = (1 - \beta) \frac{\alpha}{1 - \alpha} \quad (4)$$

$$\gamma_2 = -(1 - \beta) \frac{\alpha}{1 - \alpha} \quad (5)$$

$$\mu_i = -(1 - \beta) \ln A(0)_i \quad (6)$$

$$\eta_t = g(t_2 - \beta t_1) \quad (7)$$

where $A(0)_i$ represents the initial level of technology, and s, n, δ are, respectively, the saving rate, the population growth rate, the depreciation rate; g is the exogenous rate of technological change,⁷ assumed to be invariant across individual economies; α is the usual capital share of a standard Cobb-Douglas production function; finally, $\beta \equiv e^{-\lambda\tau}$, where $\lambda = (1 - \alpha)(n + g + \delta)$ represents the convergence parameter and $\tau \equiv t_2 - t_1$ is the time span considered.

In this specification, technology is represented by two terms. The first term, μ_i , is a time-invariant component that varies across economies and should control for various unobservable

⁶ See also Caselli *et al.* (1996) and Islam (2003) among others.

⁷ As is standard in this literature, $(g + \delta)$ is assumed equal to 0.05.

factors. The second is the time trend component (eq. 7) that captures the growth rate of the technology frontier assumed constant across individuals. Once we have the estimated individual intercepts, we can obtain an index of TFP by computing:

$$A(0)_i = \exp\left(\frac{\mu_i}{1-\beta}\right) \quad (8)$$

Since TFP estimates include all unobservable components assumed to be different across countries but constant over time such as technology gaps (more on this presently), culture and institutions, and since these components are likely to be correlated with other regressors, a fixed effect estimator is appropriate. If we apply LSDV to equation (1), individual effects may be directly estimated. With other estimators, such as Within Group or Arellano-Bond (1991), estimates of μ_i and, thus, of $\hat{A}(0)_i$ can be obtained through equation (1) by:

$$(\hat{\mu}_i + \hat{u}_{it}) = y_{it} - \beta y_{it-\tau} - \sum_{j=1}^2 \hat{\gamma}_j x_{j,it} \quad (9)$$

$$\hat{\bar{\mu}}_i = \frac{1}{T} \sum (\hat{\mu}_i + \hat{u}_{it}) \quad (10)$$

The main problem with this methodology is that, while it was designed to control for the presence of cross-region TFP heterogeneity, it rules out technology convergence by assumption. More precisely, equation (1) is obtained by log-linearizing the Solow model around the steady-state under the assumption of a stationary degree of TFP heterogeneity. In other words, technology in all economies is assumed to grow at the same rate whatever their position relative to the world frontier. This is in sharp contrast with the technological catch-up hypothesis. In the latter, a country's "technology gap" – if higher than its stationary value⁸ – may enhance its TFP growth rate during the transition towards a steady state in which all economies will grow at the common rate g . As a consequence, a high degree of cross-country technology differentials is likely to be the source of TFP convergence.

Hence, how can we use equation (1) to test for the presence/absence of technological convergence? The solution is to estimate TFP values over several subsequent periods, in order to test whether the observed time pattern is consistent either with the catch-up hypothesis or with the alternative hypothesis that the current degree of technology heterogeneity is at its stationary value.⁹

⁸ In models of technology catch-up, stationary values of technology gaps are determined by differences in the countries' fundamentals. If the follower countries' gaps are beyond their stationary values, cross-country TFP dynamics should be characterized by a process of conditional convergence. More on this in section 5 below.

⁹ Splitting a longer period in several subperiods has an additional advantage, since the longer the time dimension of the panel, the higher the risk that differences in TFP levels are not constant due to the presence of technological diffusion. In other words, equation (1) is likely to be an approximation of the real process – an approximation that deteriorates as the length of the period under analysis increases.

To this aim we further develop an approach first suggested by Islam (2003). However, in our choice of estimators, we do not include the system-GMM suggested by Blundell and Bond (1998) and Minimum Distance, both used by Islam (2003). Reasons for this choice are as follows. First of all, the theoretical restrictions on which the system-GMM estimator is based do not hold in this context.¹⁰ Second, the use of the Minimum Distance estimator has been highly criticised within the growth literature and there is a lack of empirical analysis that compares the performance of this estimator with other available estimators¹¹. In other words, the use of the Minimum Distance and system GMM to estimate fixed effects, and thus TFP levels do not represent an optimal choice in this context. Further, we use our TFP estimates to perform an analysis of the determinants of productivity not developed in his paper.

Our period of analysis, from 1985 to 2006 includes some years which have been strongly influenced by the introduction of IT technologies. In terms of TFP convergence, such years are important since the development of IT have seen "... a rapidly rising source of aggregate productivity growth throughout the 1990's".¹² More precisely, we use different datasets (Cambridge Econometrics and Eurostat) to estimate the following equation:

$$\tilde{y}_{it} = \beta \tilde{y}_{it-\tau} + \sum_{j=1}^3 \gamma_j \tilde{x}_{j,it-\tau} + \mu_i + u_{it} \quad (11)$$

$$\tilde{y}_{it} = y_{it} - \bar{y}_t, \quad \tilde{x}_{it} = x_{it} - \bar{x}_t \quad (12)$$

where \bar{y}_t and \bar{x}_t are the EU regional averages in period t : that is, data are taken in difference from the sample mean, in order to control for the presence of a time trend component η_t and of a likely common stochastic trend (the common component of technology) across countries.¹³ We use a three-year time span in order to control for business cycle fluctuations and serial correlation, which are likely to affect the data in the short run. Moreover, the use of a three-year time span enables us to apply all available observations and obtain a sample with $T=8$, which is the longest possible one.¹⁴ Finally, all regressors are taken at their $t-3$ level to control for likely endogeneity problems.

¹⁰ In particular, this methodology requires that first-difference Δy_{it} are not correlated with μ_i (see Bond *et al.*, 2001), and this implies that in order to implement this estimator we need to assume the absence of technological catching-up. If efficiency growth is related to initial efficiency, the first difference of log output might be correlated with the individual effect. On this see also Hauk and Wacziarg (2004).

¹¹ For more on the use of the MD estimator in growth analysis see Caselli *et al.* (1996) and Islam (2003).

¹² See Jorgenson (2005).

¹³ The Levin *et al.* (2002) panel unit-root test performed on the demeaned GDP series reject the hypotheses that series are nonstationary.

¹⁴ Therefore, our sample includes the following years: 1985, 1988, 1991, 1994, 1997, 2000, 2003 and 2006.

3. Estimating cross-region TFP levels in dynamic panel: small sample problems

The first problem to solve when estimating a dynamic panel data model such as the one represented by equation (11) is the selection of the best estimator. The answer is not simple since even consistent estimators are characterized by small sample problems. To this end we carefully compare the results obtained by using three different fixed effects estimators: LSDV, Arellano and Bond (1991) and Kiviet (1995).

As we specify above, our panel includes the period 1985-2006 for 199 regions. Using the three-year time span (or $\tau = 3$) implies that we are left with $T=8$ observations for each region. Estimates over the whole sample period are reported in Table 1. For each regression we include both our estimates and the implied value of the structural parameter $\hat{\lambda}$, i.e. the speed of the convergence parameter.

In analysing our results, we follow the procedure proposed by Bond *et al.* (2001) and consistent with the literature on partial identification¹⁵. Their suggestion is to use the results obtained with LSDV and a pooling OLS estimator as benchmarks to detect a possible bias in our other estimates. In particular, results show that in dynamic panels the OLS coefficient in the lagged dependent variable is known to be biased upwards. Conversely, LSDV, while consistent for large T, is characterised by small sample problems and it is known to produce downward biased estimates on the AR(1) coefficient in small samples. Therefore, in our specific case, since we presume that the true parameter value lies somewhere between $\hat{\beta}_{ols}$ and $\hat{\beta}_{LSDV}$, we expect it to be between 0.98 and 0.60 (as shown in Table 1) and we will exclude from our analysis estimators that produce results out of this range.

When equation (11) is estimated with LSDV (Model 2) we find, as said above, an AR(1) coefficient of 0.60 and a correspondingly speed of convergence of 1.7%. Among the regressors, both the coefficients on the lagged dependent variable and on population growth are significant and have the expected sign, while the coefficient on human capital is not significant.¹⁶ These results will be confirmed when other estimation procedures are used.

Our third estimator is based on Kiviet (1995), a paper that addresses the problem of the LSDV finite sample bias by proposing a small sample correction. As expected, the use of the Kiviet correction procedure increases the LSDV parameter. In Model 3 (KIVIET), the coefficient of the lagged dependent variable is 0.74, with a decrease in the corresponding speed of convergence

¹⁵ As Manski (2007) puts it, “a parameter is partially identified if the sampling process and maintained assumptions reveal that the parameter lies in a set, its ‘identification region’, that is smaller than the logical range of the parameter but larger than a single point”.

¹⁶ The lack of empirical support for human capital in convergence regressions based on large international datasets is a well known problem. A number of possible explanations have been put forward. See Pritchett (1996), Temple (1999), and Krueger and Lindhal (2001).

coefficient to approximately 1%. Clearly KIVLET satisfies the aforementioned Bond *et al.* (2001) criterion since the estimated AR(1) coefficient lies between $\hat{\beta}_{ols}$ and $\hat{\beta}_{LSDV}$.¹⁷

Let us now extend our comparison to the GMM-AB estimator¹⁸. This may be performed under very different assumptions about the endogeneity of the included regressors. In this study we adopt three different hypotheses on the additional regressors x 's. First, Model 4 (GMM-AB1) in Table 1 assumes that all x 's are strictly exogenous; secondly, Model 5 (GMM-AB2) assumes instead that all regressors are endogenous; finally, Model 6 (GMM-AB3) assumes predetermined regressors. While the estimated AR(1) coefficients do not suggest any presence of bias, conversely, the Sargan test in each of the three models implies that these specifications are not valid. Further, the estimated coefficients of the lagged dependent variable never satisfy the Bond *et al.* (2001) criterion: only GMM-AB1 has an estimated AR(1) coefficient almost identical to the lowest interval value, that is, $\hat{\beta}_{LSDV}$. As a consequence, in the remaining part of the paper we do not further use or report results based on this estimator.

Table 1. Panel estimations

Sample: 199 regions EU, (1985'(2006)						
Dependent Variable: per capita gdp level						
Observations: 1393						
	I	II	III	IV	V	VI
	OLS	LSDV	KIVLET	GMM-AB1	GMM-AB2	GMM-AB3
$\tilde{y}_{it-\tau}$	0.977*** (0.004)	0.599*** (0.021)	0.742*** (0.026)	0.599*** (0.055)	0.492*** (0.05)	0.557*** (0.047)
$\tilde{x}_{1,it-\tau}$	-0.005 (0.005)	0.041*** (0.01)	0.038*** (0.011)	0.017 (0.013)	0.088*** (0.023)	0.062*** (0.017)
$\tilde{x}_{2,it-\tau}$	0.011 (0.013)	0.027 (0.017)	0.011 (0.018)	0.023 (0.019)	0.008 (0.03)	0.077*** (0.019)
λ	0.008	0.171	0.099	0.171	0.236	0.195
Sargan test (p-value)				0	0	0
AB-2 test (p-value)				0.39	0.11	0.16

Note: standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1

With the remaining estimates in hand, we can, therefore, compute the TFP measures. In our LSDV estimates the regional dummy coefficients, $\hat{\mu}_i$, are almost invariably statistically significant. In particular, the F-test of the joint hypothesis that all the coefficients on our dummies are equal to

¹⁷ The analysis is performed assuming a bias correction up to order $O(1/T)$ and Anderson Hsiao as consistent estimator in the first step. Results are not sensitive to the use of alternative options: the Spearman rank order coefficient obtained comparing TFP obtained with KIVLET (Anderson-Hsiao) and KIVLET(Arellano-Bond) is extremely high, 0.997. Standard errors are calculated through bootstrapping.

¹⁸ Note that Blundell and Bond (1998) and Bond *et al.* (2001) show that, when T is small, and either the autoregressive parameter is close to one (highly persistent series), or the variance of the individual effect is high relative to the variance of the transient shock, then even the GMM-AB estimator is downward biased.

zero is 23.15 (p-value=0.00) and clearly rejects the hypothesis of no difference among regions.¹⁹ We obtain estimates of $\hat{A}(0)_i$ by means of eq. (8). In all cases, the TFP estimates $\hat{A}(0)_i$ are then used to compute $T\tilde{F}P_i = \hat{A}(0)_i / \hat{A}(0)_{DK}$, with $\hat{A}(0)_{DK}$ being the estimated TFP value for Denmark. As we shall see, in our analysis this country/region is consistently estimated as the TFP leader. Table A1 in the Appendix shows the ranking of each region's TFP relative to Denmark, based respectively on LSDV and KIVIET together with a ranking based on a VA per capita in 1960 reported as a benchmark. The Spearman rank order coefficient shows that the TFP rankings remain rather constant across the two estimators and both are similar to the regional ranking obtained using the initial level of per capita Value Added (VA85 henceforth). In particular, the Spearman coefficient between LSDV and KIVIET is 0.99, between KIVIET and VA85 is 0.95, and between LSDV and VA85 is 0.93.

A closer inspection of our estimates would further reveal that best and worst performers are almost identical across the two estimators, as shown by the data reported in tables 2a and 2b. These tables confirm some well known stylized facts, with the northern EU regions at the top of the technology ladder and southern ones at the bottom. First of all, as far as the leader regions are concerned, after Denmark we find four capital areas, that is Inner London, Zurich, Oslo and Brussels. Secondly, our twenty TFP laggards regions are all in southern Europe, that is in Italy, Spain, Portugal and Greece.

To sum up, the pattern and the magnitude of TFP heterogeneity, as measured by our estimates, strongly confirm that cross-region TFP differences are wide and that they are strongly associated with the cross-region differences in per capita VA. That is, a potential for technological catch-up does exist for the lagging regions. In the next section we will estimate TFP at two points in time to assess to what extent that potential has materialized as an actual source of convergence.

¹⁹ Note that individual effects are not directly estimated when GMM-AB1 and KIVIET are used.

Table 2a: Relative TFP levels (per capita): best 20 regions

Relative TFP levels (per capita) – BEST 20			
LSDV		KIVIET	
DENMARK	1.00	DENMARK	1.00
Inner London	0.76	Inner London	0.66
Zurich	0.68	Zurich	0.57
Oslo og Akershus	0.62	Oslo og Akershus	0.51
LUXEMBOURG	0.60	Bruxelles-Brussel	0.50
Bruxelles-Brussel	0.59	LUXEMBOURG	0.47
Nordwestschweiz	0.54	Nordwestschweiz	0.42
Zentralschweiz	0.51	Hamburg	0.41
Hamburg	0.50	Region Lemanique	0.39
Region Lemanique	0.50	Zentralschweiz	0.38
Stockholm	0.47	Stockholm	0.36
Ostschweiz	0.45	Ostschweiz	0.33
Ticino	0.44	Ile de France	0.33
Espace Mittelland	0.44	Ticino	0.32
Ile de France	0.44	Espace Mittelland	0.32
Berkshire, Buckinghamshire and Oxfordshire	0.43	Wien	0.31
North Eastern Scotland	0.42	Bremen	0.30
Wien	0.41	Berkshire, Buckinghamshire and Oxfordshire	0.30
Darmstadt	0.41	Oberbayern	0.30
Bremen	0.41	Darmstadt	0.29

Table 2b: Relative TFP levels (per capita): worst 20 regions

Relative TFP levels (per capita) – WORST 20			
LSDV		KIVIET	
Ipeiros	0.10	Ipeiros	0.04
Dytiki Ellada	0.10	Norte	0.04
Anatoliki Makedonia	0.10	Centro (P)	0.05
Centro (P)	0.11	Dytiki Ellada	0.05
Norte	0.11	Anatoliki Makedonia	0.05
Peloponnisos	0.11	Alentejo	0.05
Thessalia	0.12	Peloponnisos	0.05
Extremadura	0.12	Extremadura	0.05
Alentejo	0.12	Thessalia	0.06
Ionia Nisia	0.12	Ionia Nisia	0.06
Dytiki Makedonia	0.13	Algarve	0.06
Kentriki Makedonia	0.14	Dytiki Makedonia	0.07
Voreio Aigaio	0.14	Voreio Aigaio	0.07
Kriti	0.14	Kentriki Makedonia	0.07
Andalucia	0.14	Kriti	0.07
Algarve	0.14	Andalucia	0.07
Calabria	0.15	Castilla-la Mancha	0.07
Castilla-la Mancha	0.15	Galicia	0.07
Galicia	0.15	Calabria	0.07
Murcia	0.16	Murcia	0.08

4. Detecting technological convergence: Empirical results

To detect how much TFP convergence is present in our sample, we estimate TFP using the same methodology over two sub-periods: 1985-1997 and 1997-2006. Estimating TFP-levels for our two sub-periods, both with $T=5$, further exacerbates the problems associated with small sample bias. In such conditions Monte Carlo results show that KIVIET should be preferred over the other estimators.²⁰ Results find that for balanced panel and small (less or equal to ten) or moderate T ($T=30$), such as the one we usually find in convergence literature, LSDV estimates corrected for the bias (KIVIET from now on) have more attractive properties than other available estimators.²¹

As before, we estimate equation (11) and save the two different series of $\hat{\mu}_i$. Results are shown in Table 3, where we focus on the KIVIET estimates of the AR (1) coefficient even though the OLS and LSDV estimates are also shown for comparative reasons and to get the two bounds for the Bond et al. criterion.

The convergence coefficient is significant in both sub-periods and assumes an implausible high value for the first sub-period. Moreover, the KIVIET AR(1) coefficient stays within the estimated upper (OLS) and lower (LSDV) bounds in both sub-periods. The remaining regressors are significant and with the expected sign only in the second sub-periods while for the first sub-period savings are non significant in most cases and $\ln(n + \delta + g)$ shows a positive sign. As before, $\hat{\mu}_i$ are almost invariably significant in both cases. A test enables us to reject the hypothesis of no difference between regions for both sub-periods. The value of the F-test for the joint hypothesis that all the coefficients on our regional dummies are equal to zero is 51.6 for the first sub-period (p-value 0.00), and 16.79 for the second one (p-value 0.00).

Again, we apply equation (8) to our KIVIET estimates to obtain two series of $\hat{A}(0)_i$, and then compute the two indexes $T\tilde{F}P_{i,1} = \hat{A}_{i,1} / \hat{A}_{DK,1}$ (for the initial period, 1985-97) and $T\tilde{F}P_{i,2} = \hat{A}_{i,2} / \hat{A}_{DK,2}$ (for the subsequent period, 1997-2006). Our estimated TFP values for the two sub-periods, and the change of the ranking of the twenty best and worst performing region, are shown in Table A2 in the Appendix.

²⁰ See Kiviet, 1995; Judson and Owen, 1999, Everaert and Pozzi, 2007. An exception can be found in Hauk and Wacziarg (2004) that suggest the use of a between estimator when measurement error is present. However, surprisingly, in their Monte Carlo analysis they do not consider the Kiviet estimator that is the preferred one in all other studies.

²¹ In particular, these studies find that for $T \leq 20$ and $N \leq 50$, the KIVIET and Anderson-Hsiao estimators consistently outperform GMM-AB. Moreover, despite having a higher average bias, KIVIET turns out to be more efficient than Anderson-Hsiao.

Table 3. Panel estimations

Sample: 199 regions EU, 3 years time-span						
Dependent Variable: $\ln(y_{i,t})$ demeaned						
Observations 796						
	1985-1997			1997-2006		
	OLS	LSDV	KIVIET	OLS	LSDV	KIVIET
$\tilde{y}_{it-\tau}$	0.9735*** (0.006)	0.2314*** (0.032)	0.3779** (0.042)	0.9847*** (0.004)	0.6489*** (0.029)	0.8814*** (0.038)
$\tilde{x}_{1,it-\tau}$	-0.0134* (0.007)	0.0180 (0.019)	0.0196 (0.019)	0.0007 (0.005)	0.0348*** (0.011)	0.0237*** (0.011)
$\tilde{x}_{2,it-\tau}$	0.0123 (0.019)	0.0671*** (0.023)	0.0724*** (0.024)	-0.0324** (0.013)	-0.0859*** (0.020)	-0.0950*** -0.022
λ	0.009	0.488	0.324	0.005	0.144	0.042

Note: standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We start this analysis by examining the whole distribution over the two sub-periods. The main characteristic of our TFP distributions is the absence of a clear overall process of TFP convergence. When one compares the values of the standard deviation for the two series of initial and subsequent TFP, we observe that TFP dispersion is almost constant across the two sub-periods (standard deviation is 0.116 and 0.143, respectively). This lack of overall TFP convergence (or, if any, a slight divergence) is confirmed by Figure 1, which illustrates the absence of significant changes in the distribution between the initial TFP levels (dotted line) and subsequent TFP levels (straight line). In both periods, a single-peak pattern does characterize the distribution, with a few more advanced countries separating themselves from the rest. Results are robust with respect to the use of per worker data instead of per capita ones as reported in figure 2.

Figure 1: distribution of TFP levels (per capita)

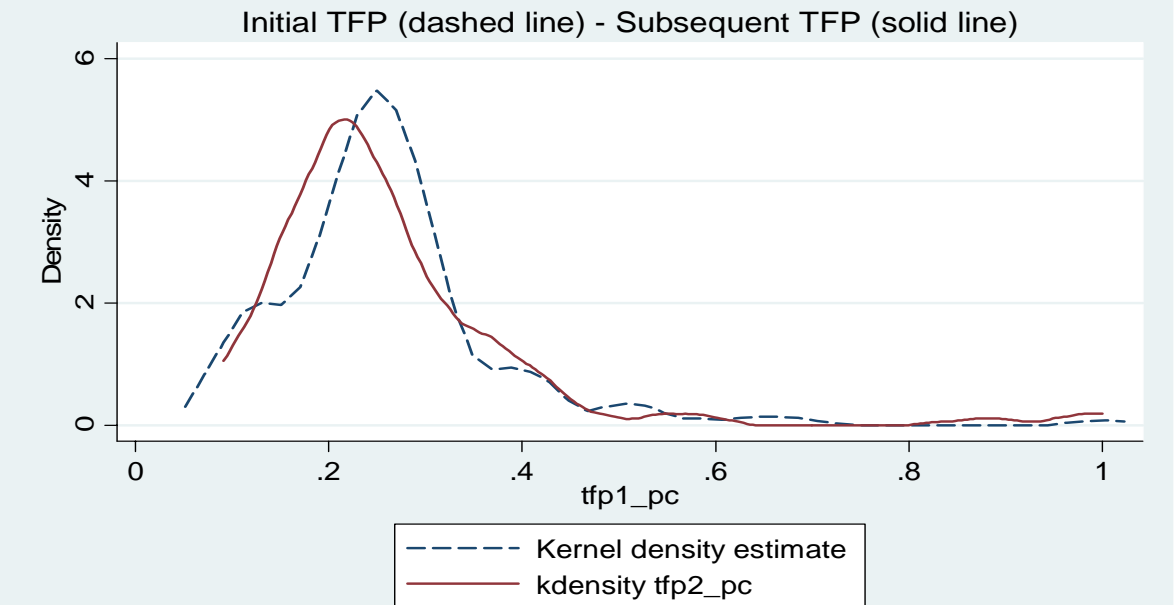
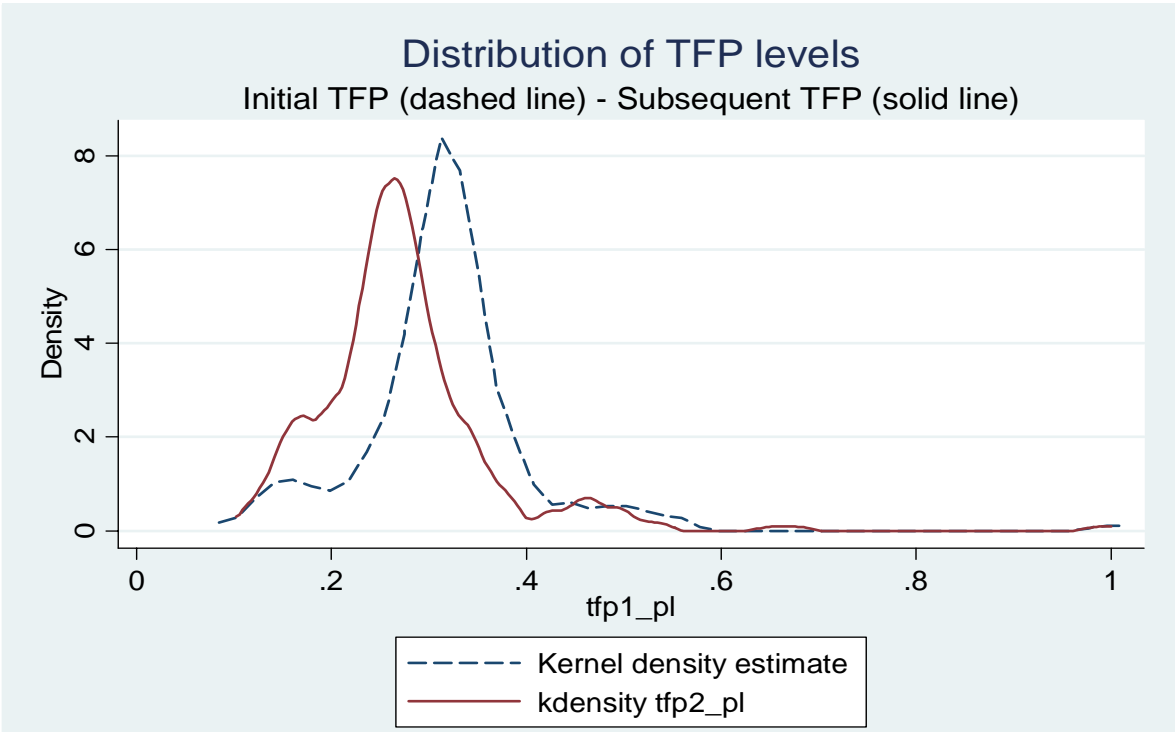
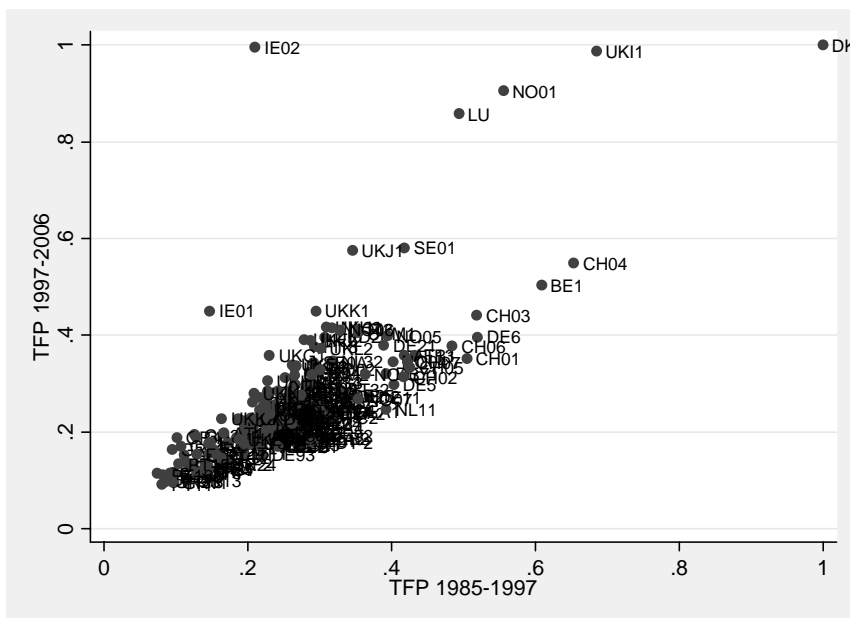


Figure 2: distribution of TFP levels (per worker)



However, as it is well known, this absence of dynamics may, in fact, hide complex and interesting intra-distribution dynamic patterns. Before analysing the intra-distribution dynamic, it is worth noticing that in our estimates the Denmark is always in the leading position in both periods. Figure 3 shows the relationship between the two-period TFP estimates in our whole sample of regions. The 45 degree line shows the locus where each region's relative (to Denmark) TFP level would be time-invariant. Since most regions are below the 45 degree line, they have clearly underperformed with respect to the Denmark in terms of TFP growth. Only few regions seems to be significantly improving with respect to Denmark's performance. Not surprisingly among these regions one finds the two Irish regions.

Figure 3



Further, when we look at the detailed regional data we find that the intra-distribution dynamics across EU regions has been remarkable. For the twenty best and worst performing region in Table 2A we include both the first and second sub-period ranking position in terms of relative TFP levels and in the last two columns we include the change of rank in relative TFP levels and that observed in per capita VA levels between the initial and the final observation. Data show as EU regions have experienced significant changes of rank. Among the losers we mainly find German, Italian and Netherland regions: Rheinhessen-Pfalz and Trentino (-100 positions), Hannover (-98), Arnsberg (-93), Groningen (-63). Conversely, with the exception of Ireland, among the winners results are less region specific but we identify many UK regions: Border (160), Southern and Eastern (+140), Herefordshire (+89), Northern Ireland (+85) and Madrid (+75) are the best performers.

Notice that the observed changes in the rankings of TFP and of VA per capita, despite being highly correlated (0.81) are not identical. Nevertheless, the association between TFP and VA per capita is noteworthy: countries that have significantly improved in their TFP ranking are also the countries which have achieved high growth in VA per capita. That is, while obtaining fast growth in TFP is not simple, it appears to be a key factor in achieving fast VA per capita growth.

The robustness of these results has been assessed by using VA per worker instead of per capita levels and a different estimator. In particular, almost identical results have been obtained replicating the whole analysis using LSDV estimates of $T\tilde{F}P_i$.

7. Conclusions

The main aim of this paper is to assess the existence of technology convergence across a sample of 199 European regions between 1985 and 2006. Different methodologies have been proposed to measure TFP heterogeneity across countries, but only a few of them try to capture the presence of technology convergence as a separate component from the standard (capital-deepening) source of convergence. To distinguish between these two components of convergence, we have proposed and applied a fixed-effect panel methodology. Robustness of results is assessed using different estimation procedures such as simple LSDV, Kiviet-corrected LSDV, and GMM *à la* Arellano and Bond (1991).

Our empirical analysis confirms the presence of a high and persistent level of TFP heterogeneity across regions. Furthermore, we do not find evidence of a global process of TFP convergence, since the dispersion of the estimated TFP levels remained constant through time. Within this aggregate persistence, important changes are nevertheless detected.

In general, the links between the micro and macro levels of TFP analysis need to be further developed and this may be considered as one of the main challenges currently facing this literature.

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APPENDIX

TABLE A1. Rank of relative TFP levels and per capita Value added (Vapc85) in 1985

Code	Regions	TFP Ranking (LSDV)	TFP Ranking (KIVIET)	Vapc85 Ranking
BE1	Bruxelles-Brussel	6	5	4
BE2	Vlaams Gewest	81	86	100
BE3	Region Walonne	157	156	152
DK	DENMARK	1	1	1
DE11	Stuttgart	26	26	23
DE12	Karlsruhe	32	30	29
DE13	Freiburg	70	66	50
DE14	Tubingen	53	53	45
DE21	Oberbayern	21	19	24
DE22	Niederbayern	77	79	79
DE23	Oberpfalz	66	70	80
DE24	Oberfranken	67	67	67
DE25	Mittelfranken	36	35	30
DE26	Unterfranken	68	71	77
DE27	Schwaben	58	57	49
DE5	Bremen	20	17	18
DE6	Hamburg	9	8	6
DE71	Darmstadt	19	20	27
DE72	Giessen	103	98	75
DE73	Kassel	78	78	65
DE91	Braunschweig	89	82	54
DE92	Hannover	71	68	43
DE93	Luneburg	150	149	122
DE94	Weser-Ems	112	110	93
DEA1	Dusseldorf	38	33	26
DEA2	Koln	51	46	35
DEA3	Munster	114	109	89
DEA4	Detmold	76	74	61
DEA5	Arnsberg	85	77	42
DEB1	Koblenz	131	114	78
DEB2	Trier	134	130	91
DEB3	Rheinhausen-Pfalz	87	76	32
DEC	Saarland	92	84	63
DEF	Schleswig-Holstein	96	96	88
GR11	Anatoliki Makedonia	197	195	180
GR12	Kentriki Makedonia	188	186	184
GR13	Dytiki Makedonia	189	188	183
GR14	Thessalia	193	191	190
GR21	Ipeiros	199	199	195
GR22	Ionia Nisia	190	190	192
GR23	Dytiki Ellada	198	196	193
GR24	Stereia Ellada	171	165	146
GR25	Peloponnisos	194	193	187
GR3	Attiki	174	173	179
GR41	Voreio Aigaio	187	187	191
GR42	Notio Aigaio	177	179	182
GR43	Kriti	186	185	189
ES11	Galicia	181	182	185

TABLE A1 (Continue)

Code	Regions	TFP Ranking (LSDV)	TFP Ranking (KIVIET)	Vapc85 Ranking
ES12	Asturias	176	174	171
ES13	Cantabria	168	169	169
ES21	País Vasco	141	147	155
ES22	Navarra	140	145	154
ES23	Rioja	161	160	158
ES24	Aragon	162	162	166
ES3	Madrid	123	136	156
ES41	Castilla-Leon	170	171	174
ES42	Castilla-la Mancha	182	183	186
ES43	Extremadura	192	192	194
ES51	Cataluna	148	151	162
ES52	Com. Valenciana	169	170	167
ES53	Baleares	156	155	153
ES61	Andalucia	185	184	188
ES62	Murcia	180	180	181
ES7	Canarias	172	172	176
FR1	Ile de France	15	13	15
FR21	Champagne-Ard.	110	115	113
FR22	Picardie	149	143	125
FR23	Haute-Normandie	111	105	87
FR24	Centre	119	116	103
FR25	Basse-Normandie	146	146	139
FR26	Bourgogne	125	124	109
FR3	Nord-Pas de Calais	151	150	140
FR41	Lorraine	144	141	130
FR42	Alsace	93	90	76
FR43	Franche-Comte	132	132	123
FR51	Pays de la Loire	117	125	132
FR52	Bretagne	136	139	141
FR53	Poitou-Charentes	143	144	143
FR61	Aquitaine	121	117	105
FR62	Midi-Pyrenees	127	129	129
FR63	Limousin	142	148	148
FR71	Rhone-Alpes	88	87	81
FR72	Auvergne	139	142	144
FR81	Languedoc-Rouss.	154	153	151
FR82	Prov-Alpes-Cote d'Azur	109	107	98
FR83	Corse	155	154	147
IE01	Border	152	158	175
IE02	Southern and Eastern	30	47	159
ITC1	Piemonte	90	91	82
ITC2	Valle d'Aosta	56	52	34
ITC3	Liguria	98	101	117
ITC4	Lombardia	47	49	47
ITD1-2	Trentino-Alto Adige	113	111	57
ITD3	Veneto	95	97	95
ITD4	Friuli-Venezia Giulia	82	85	96
ITD5	Emilia-Romagna	63	59	44
ITE1	Toscana	99	100	111
ITE2	Umbria	137	138	131
ITE3	Marche	118	128	133
ITE4	Lazio	84	89	94
ITF1	Abruzzo	160	159	149

TABLE A1 (Continue)

Code	Regions	TFP Ranking (LSDV)	TFP Ranking (KIVIET)	Vapc85 Ranking
ITF2	Molise	167	166	161
ITF3	Campania	179	178	170
ITF4	Puglia	175	176	172
ITF5	Basilicata	178	177	168
ITF6	Calabria	183	181	178
ITG1	Sicilia	173	175	173
ITG2	Sardegna	166	167	164
NL11	Groningen	50	25	2
NL12	Friesland	126	135	142
NL13	Drenthe	147	131	66
NL21	Overijssel	100	108	136
NL22	Gelderland	107	119	135
NL23	Flevoland	159	161	160
NL31	Utrecht	24	29	68
NL32	Noord-Holland	33	34	33
NL33	Zuid-Holland	57	60	74
NL34	Zeeland	102	102	101
NL41	Noord-Brabant	60	73	107
NL42	Limburg (NL)	94	99	126
AT11	Burgenland	163	163	163
AT12	Niederosterreich	138	137	120
AT13	Wien	18	16	11
AT21	Karnten	130	118	97
AT22	Steiermark	129	120	108
AT31	Oberosterreich	97	83	52
AT32	Salzburg	42	39	28
AT33	Tirol	74	63	36
AT34	Vorarlberg	64	54	39
PT11	Norte	195	198	199
PT16	Centro (P)	196	197	198
PT17	Lisboa	165	168	177
PT18	Alentejo	191	194	197
PT15	Algarve	184	189	196
FI13	Ita-Suomi	153	152	150
FI18	Etela-Suomi	40	40	51
FI19	Lansi-Suomi	116	113	110
FI1A	Pohjois-Suomi	120	121	127
FI2	Aland	23	24	25
SE01	Stockholm	11	11	17
SE02	Ostra Mellansverige	72	69	62
SE04	Sydsverige	46	45	53
SE06	Norra Mellansverige	69	65	64
SE07	Mellersta Norrland	48	44	40
SE08	Ovre Norrland	55	50	41
SE09	Smaland med oarna	54	55	55
SE0A	Vastsverige	41	41	48
UKC1	Tees Valley and Durham	135	134	115
UKC2	Northumberland and Tyne and Wear	105	103	114
UKD1	Cumbria	101	95	71
UKD2	Cheshire	31	37	58
UKD3	Greater Manchester	65	61	73
UKD4	Lancashire	91	92	99
UKD5	Merseyside	145	140	121

TABLE A1 (Continue)

Code	Regions	TFP Ranking (LSDV)	TFP Ranking (KIVIET)	Vapc85 Ranking
UKE1	East Riding and North Lincolnshire	83	88	106
UKE2	North Yorkshire	75	81	102
UKE3	South Yorkshire	133	123	112
UKE4	West Yorkshire	59	64	90
UKF1	Derbyshire and Nottinghamshire	80	80	84
UKF2	Leicestershire, Rutland and Northamptonshire	43	48	70
UKF3	Lincolnshire	122	127	134
UKG1	Herefordshire, Worcestershire and Warwickshire	79	94	138
UKG2	Shropshire and Staffordshire	108	112	128
UKG3	West Midlands	49	56	72
UKH1	East Anglia	73	75	86
UKH2	Bedfordshire and Hertfordshire	28	31	46
UKH3	Essex	104	104	124
UKI1	Inner London	2	2	3
UKI2	Outer London	62	72	104
UKJ1	Berkshire, Buckinghamshire and Oxfordshire	16	18	38
UKJ2	Surrey, East and West Sussex	37	42	83
UKJ3	Hampshire and Isle of Wight	61	62	85
UKJ4	Kent	115	126	137
UKK1	Gloucestershire, Wiltshire and North Somerset	29	36	69
UKK2	Dorset and Somerset	106	106	119
UKK3	Cornwall and Isles of Scilly	164	164	165
UKK4	Devon	124	122	118
UKL1	West Wales and The Valleys	158	157	157
UKL2	East Wales	34	38	60
UKM1	North Eastern Scotland	17	22	59
UKM2	Eastern Scotland	52	51	56
UKM3	South Western Scotland	86	93	116
UKM4	Highlands and Islands	45	58	92
UKN	Northern Ireland	128	133	145
NO01	Oslo og Akershus	4	4	7
NO02	Hedmark og Oppland	44	43	37
NO03	Sor-Ostlandet	35	27	16
NO04	Agder og Rogaland	25	23	9
NO05	Vestlandet	22	21	14
NO06	Trondelag	27	28	31
NO07	Nord-Norge	39	32	19
CH01	Region Lemanique	10	9	8
CH02	Espace Mittelland	14	15	22
CH03	Nordwestschweiz	7	7	10
CH04	Zurich	3	3	5
CH05	Ostschweiz	12	12	20
CH06	Zentralschweiz	8	10	13
CH07	Ticino	13	14	21
LU	LUXEMBOURG	5	6	12

TABLE A2

Ranking changes: worst performers

cod_reg	name_reg	TFP ranking		Change of rank relative TFP	Change of rank (per capita GDP)
		first subperiod	second subperiod		
DEB3	Rheinessen-Pfalz	49	149	-100	-59
<i>ITD1-2</i>	<i>Trentino-Alto Adige</i>	<i>54</i>	<i>154</i>	<i>-100</i>	<i>3</i>
DE92	Hannover	43	141	-98	-45
DEA5	Arnsberg	57	150	-93	-56
DE91	Braunschweig	67	153	-86	-43
DEA3	Munster	95	162	-67	-44
DEB1	Koblenz	98	165	-67	-52
<i>ITC2</i>	<i>Valle d'Aosta</i>	<i>35</i>	<i>102</i>	<i>-67</i>	<i>-32</i>
NL11	Groningen	20	83	-63	-39
NL13	Drenthe	103	166	-63	-81
DEA4	Detmold	62	124	-62	-26
DEA1	Dusseldorf	30	90	-60	-19
DEA2	Koln	37	96	-59	-29
DE24	Oberfranken	61	118	-57	-12
DEC	Saarland	75	132	-57	-18
DEF	Schleswig-Holstein	77	134	-57	-20
<i>ITC1</i>	<i>Piemonte</i>	<i>73</i>	<i>128</i>	<i>-55</i>	<i>-23</i>
<i>ITD5</i>	<i>Emilia-Romagna</i>	<i>41</i>	<i>94</i>	<i>-53</i>	<i>-31</i>
DEB2	Trier	111	163	-52	-43
<i>ITC4</i>	<i>Lombardia</i>	<i>38</i>	<i>88</i>	<i>-50</i>	<i>-23</i>
<i>FR26</i>	<i>Bourgogne</i>	<i>108</i>	<i>156</i>	<i>-48</i>	<i>-31</i>
DE14	Tubingen	46	92	-46	-14
DE27	Schwaben	47	93	-46	-9
DE73	Kassel	71	116	-45	-18
DE11	Stuttgart	23	65	-42	-8
NO07	Nord-Norge	27	69	-42	-29
DE13	Freiburg	60	101	-41	-24
DE93	Luneburg	133	174	-41	-36
<i>FR21</i>	<i>Champagne-Ard.</i>	<i>110</i>	<i>151</i>	<i>-41</i>	<i>-18</i>
<i>FR42</i>	<i>Alsace</i>	<i>74</i>	<i>115</i>	<i>-41</i>	<i>-33</i>

Ranking changes: best performers

cod_reg	name_reg	TFP ranking		Change of rank relative TFP	Change of rank (per capita GDP)
		first subperiod	second subperiod		
FI19	Lansi-Suomi	121	81	40	8
UKJ3	Hampshire and Isle of Wight	78	36	42	38
UKJ4	Kent	128	86	42	33
GR3	Attiki	181	137	44	10
UKD5	Merseyside	147	103	44	-14
GR41	Voreio Aigaio	189	144	45	15
UKD3	Greater Manchester	83	38	45	17
UKF2	Leicestershire, Rutland	66	21	45	26
ES51	Cataluna	157	111	46	19
UKF3	Lincolnshire	125	77	48	2
UKM3	South Western Scotland	104	56	48	38
UKE2	North Yorkshire	96	46	50	18
UKE3	South Yorkshire	135	85	50	-2
FR51	Pays de la Loire	132	80	52	13
NL23	Flevoland	159	106	53	9
UKE4	West Yorkshire	88	35	53	33
UKG2	Shropshire and Staffordshire	126	68	58	18
UKK2	Dorset and Somerset	122	60	62	18
UKK3	Cornwall and Isles of Scilly	166	104	62	4
UKC2	Northumberland and Tyne	119	55	64	32
FI1A	Pohjois-Suomi	137	66	71	37
UKH3	Essex	120	47	73	32
ES3	Madrid	146	71	75	38
UKN	Northern Ireland	143	58	85	34
UKG1	Herefordshire, Worcestershire and	118	29	89	65
IE02	Southern and Eastern	142	2	140	148
IE01	Border	170	10	160	75