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Relative Sources of European Regional Productivity Convergence: A Bootstrap Frontier Approach*

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Abstract: This paper addresses the issue of Western European regional productivity growth and convergence by means of Data Envelopment Analysis (DEA), decomposing labour productivity into efficiency change, technical change and capital accumulation. The decomposition shows that most regions have fallen behind the production frontier in efficiency and that capital accumulation has had

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a diverging effect on the labour productivity distribution. Using bootstrapping methods, the paper also accounts for the inherent bias and the stochastic elements in the efficiency estimation. It is found that the relative ranking of the efficiency scores remains stable after the bias-correction, even after controlling for spatially correlated measurement errors, and that the DEA successfully identifies the regions on the production frontier as significantly more efficient than other regions.

JEL Classification: C14, C15, O47, R11

Keywords: Bootstrap, DEA, Efficiency, Regional Convergence

Les sources relatives de convergence de la productivité régionale européenne: une méthode “bootstrap”.

Enflo & Hjertstrand

A partir de la DEA (Data Envelopment Analysis), cet article cherche à aborder la question de la croissance et de la convergence de la productivité régionale de l’Europe de l’Ouest, en décomposant la productivité du travail en le changement d’efficience, la mutation technique et l’accumulation de capital. La décomposition montre que la plupart des régions se sont laissées distancer par la frontière de production en termes de l’efficience et que l’accumulation de capital a eu un effet divergent sur la distribution de la productivité du travail. En employant des méthodes “bootstrap”, cet article cherche aussi à expliquer le biais inhérent et les éléments stochastiques dans l’estimation de l’efficience. Il s’avère que le classement relatif des scores d'efficience reste stable une fois corrigé du biais, même après avoir contrôlé les erreurs de mesure qui sont en corrélation sur le plan géographique, et que la DEA identifie avec succès les régions à la frontière de production comme étant nettement plus efficientes que ne le sont les autres régions.

"Boostrap" / DEA / Efficience / Convergence régionale

Classement JEL: C14; C15; O47; R11

Relative Quellen der regionalen Produktivitätskonvergenz in Europa: ein Bootstrap-Frontieransatz

KERSTIN ENFLO AND PER HJERTSTRAND

Abstract:

In diesem Beitrag untersuchen wir das Thema des Wachstums und der Konvergenz der regionalen Produktivität in Westeuropa mit Hilfe einer Data-Envelopment-Analyse (DEA), wobei die Arbeitsproduktivität in Effizienzänderung, technische Änderung und Kapitalakkumulation aufgegliedert wird. Aus der Aufgliederung geht hervor, dass die meisten Regionen hinsichtlich der Effizienz hinter die Produktionsfrontier gefallen

sind und dass sich die Kapitalakkumulation divergierend auf die Verteilung der Arbeitsproduktivität ausgewirkt hat. Mit Hilfe von Bootstrapping-Methoden werden in diesem Beitrag auch die inhärenten Verzerrungen und stochastischen Elemente in der Effizienzschätzung berücksichtigt. Die Ergebnisse zeigen, dass die relative Einstufung der Effizienzwerte nach einer Korrektur der Verzerrung stabil bleibt, selbst wenn auf räumlich korrelierte Messfehler kontrolliert wird, und dass die Regionen an der Produktionsfrontier durch die DEA erfolgreich als signifikant effizienter als andere Regionen identifiziert werden.

JEL Classification: C14, C15, O47, R11

Keywords:

Bootstrap

DEA

Effizienz

Regionale Konvergenz

Fuentes relativas de la convergencia de productividad regional en Europa: un enfoque de frontera Bootstrap

KERSTIN ENFLO AND PER HJERTSTRAND

Abstract:

En este artículo analizamos la cuestión del crecimiento y la convergencia de productividad regional en Europa occidental según el método de Análisis Envolvente de Datos (AED), descomponiendo la productividad laboral en un cambio de eficacia, el cambio técnico y la acumulación de capital. Esta descomposición demuestra que la mayoría de regiones se quedan por detrás de la frontera de producción en cuanto a la eficacia y que la acumulación de capital ha tenido un efecto de divergencia en la distribución de la productividad laboral. Usando métodos de bootstrap, en este artículo explicamos también el sesgo inherente y los elementos estocásticos en el cálculo de la eficacia. Observamos que una clasificación relativa de las puntuaciones de eficacia sigue estable después de corregir los valores de sesgo incluso después de comprobar si existen errores de medición correlacionados espacialmente y que el método de AED identifica con éxito las regiones sobre la frontera de la producción como significativamente más eficaces que otras regiones.

Keywords:

Bootstrap

AED

Eficacia

Convergencia regional

JEL Classification: C14, C15, O47, R11

1. Introduction

The issue of regional convergence within the European Union has attracted a great deal of attention in recent years. Several studies have reported a slowdown of convergence after 1980 (NEVEN and GOUYETTE: 1995, TONDL: 1999, FAGERBERG and VERSPAGEN: 1996) and some have argued that regions are converging into different clubs (QUAH: 1996, CORRADO et al.: 2005). This extensive convergence literature has mainly focused on convergence in regional income, but a growing number of studies have lately drawn attention to labour productivity as a key factor behind regional growth and convergence. CUADRO-ROURA et al. (2000) noted that the speed of absolute convergence (β-convergence) in labour productivity was 2.8 percent to 3.5 percent in 97 European regions between 1981 and 1990. LÓPEZ-BAZO et al. (2004) found absolute convergence to be of a similar speed, 2 to 2.4 percent a year in 108 regions from 1980 to 1996. GARDINER et al. (2004) also report that the degree of convergence in labour productivity was slow between 1980 and 2001, and that much of it seemed to take place in the boom years of the 1980s.

Investigating the sources of regional productivity differentials, EZCURRA et al. (2005) showed that the size of the physical capital stock and the amount of resources devoted to research and development are positively correlated with the external factor of the regional component (derived using shift-share analysis). In addition, LÓPEZ-BAZO et al. (2004) drew attention to the fact that regional productivity spillovers are far from negligible. These recent findings underline the need to understand how technological diffusion and differences in physical capital stocks affect regional productivity growth and convergence. Our study continues the regional productivity convergence analysis by using Data Envelopment Analysis (DEA) in combination with a decomposition of labour productivity growth into three components: efficiency change, technical change and capital accumulation. The decomposition enables us to investigate the role of efficiency, technology and capital in the Western European regional productivity convergence between 1980 and 2002.

We use a data set consisting of 69 Western European regions from France, Germany, Italy, Spain and Ireland, which enables us to address the proximate causes of the regional convergence process across a larger sample of regions than has previously been used with DEA. In fact, earlier regional studies using DEA have mainly estimated efficiency and technical change for regions within a single country, not across countries. Specifically, MAUDOS et al. (2000a) and CANALETA et al. (2003) found substantial levels of inefficiency across the Spanish regions.

Originally, DEA was used in productivity analysis at the micro-level, but has recently become increasingly popular at the macro-level as a non-parametric alternative to growth accounting. The main argument for using DEA in this context is that the traditional growth accounting decomposition of technical change and factor accumulation yields biased results in the presence of inefficiency (GROSSKOPF: 1993). In addition, DEA does not require any specification of the functional form of the technology or assumption about market structure or absence of market imperfections. It does, however, require an assumption concerning the returns to scale of the technology. The non-parametric growth accounting approach was pioneered at the national level by FÄRE et al. (1994a), who decomposed labour productivity growth into efficiency and technical change. Recent contributions include the incorporation of capital accumulation into the decomposition framework (KUMAR and RUSSELL: 2002) and subsequently human capital accumulation (HENDERSON and RUSSELL: 2005). Moreover, the decomposition framework and the extension of relating the decomposed sources of labour productivity growth have increasingly been related to the question of labour productivity convergence (MAUDOS et al.: 2000b, LOS and TIMMER: 2005).

With the growing interest in the DEA-approach to growth accounting there is an increasing need to deal with its major shortcomings, i.e. the inherent bias and the failure to deal with the stochastic element of efficiency estimation. In order to overcome these deficiencies, we follow SIMAR and WILSON (1998, 2000) in using bootstrapping methods that provide the means of incorporating a stochastic element into DEA. In contrast to previous studies, the use of bootstrapping methods allows us to gauge the relative sensitivity of the estimated efficiency scores to the inherent bias of DEA. Specifically, we are interested in analyzing whether the regions' relative efficiency levels change after the bias-correction, and whether DEA is powerful enough to distinguish regions on the production frontier as significantly more efficient than the other regions in the sample.

The major findings of this paper are that the relative efficiency ranking of the regions remains stable after the bias-correction, even after controlling for spatially correlated measurement errors, and that DEA successfully identifies regions on the production frontier as significantly more efficient than most other regions in the sample. We also find that most regions have fallen behind the productivity frontier and that capital accumulation and technical change have been the two sole contributors to productivity growth on average. However, although technological advances may have benefited the initially low productive regions, capital accumulation has had a dispersed effect on the labour productivity distribution, indicating the presence of agglomeration forces in initially productive regions.

The remainder of this paper is organized as follows. The next section gives an introduction to the methodology. Section 3 provides a description of the data. Section 4 is devoted to the results, and section 5 concludes the paper.

2. Methodology

Following FÄRE et al. (1994a) and KUMAR and RUSSELL (2002) we use DEA to find the relative inefficiency levels of our regions and as a non-parametric alternative to growth accounting. Growth accounting has long been an important tool to disentangle the proximate sources of economic growth (SOLOW: 1957, GRILICHES and JORGENSON: 1967). However, the method requires several assumptions about perfect competition in markets, the functional form of the production technology in use, Hicks-neutral technological change and constant factor shares in income. Most growth accounting studies have assumed that output is produced according to a two-input Cobb-Douglas aggregate production function. This assumption was questioned by DUFFY and PAPAGEORGIOU (2000), who found that they could reject the Cobb-Douglas specification using a panel of 82 countries over a 28 year period. Furthermore, cross-country evidence suggests large variances in labour income shares of countries at various stages of development (GOLLIN: 2002). DEA is a useful method for performing growth accounting without imposing assumptions about the functional form of the technology or assuming that all regions produce output efficiently.

2.1. The DEA method

Assume that the production set is spanned by a set of input and output vectors. More formally, let $\Psi = \{(X, Y) \in \Re^{N+M}\}$. That is, the set of *N* inputs, measured by the vector *X*, can produce *M* outputs, measured by vector *Y*. All efficient production plans lie on the boundary (frontier) of the production set Ψ (DEBREU: 1959). The relative efficiency scores, λ, are calculated from a set of observations $\{(x_i, y_i); i = 1,...,n\}$ by solving a linear programming problem, where *x* and *y* denote the sample input and output vectors, respectively, and *n* denotes the number of observations in the sample (FÄRE et al.: 1994b). More precisely, the estimated DEA scores $\{\hat{\lambda}_i = \hat{\theta}_i^{-1}; i = 1,...,n\}$ of the attainable set Ψ are defined as:

$$\hat{\theta}_i(x_i, y_i) = \sup\left[\theta \middle| (x_i, \theta y_i) \in \hat{\psi}\right\}; i = 1,...,n,$$

where the subset $\hat{\psi}$ is spanned by the sample input and output vectors $\{\hat{\psi} = (x_i, y_i) \in \Re^{N+M}; i = 1,...,n\}$. SIMAR and WILSON (1998, 2000, 2006) show that $\hat{\lambda}$ is a consistent estimator, assuming that the sample observations are realizations of identically and independently distributed random variables with a monotone and continuous probability density function (See FÄRE et al.: 1994b and SIMAR and WILSON: 2006, for a detailed discussion). Further assumptions on $\hat{\psi}$ are standard in microeconomic theory; we refer to FÄRE et al. (1994b) for a comprehensive discussion.

2.2. Deficiencies with the DEA method

The DEA estimator suffers from a number of deficiencies. First, the estimator is purely deterministic, as no additive stochastic term is included in the linear programming approach. Second, the estimator is biased, since the technological frontier is only defined relative to the best practice observations in the sample. Although this procedure rules out the possibility that the "true" frontier lies below the constructed frontier, it might be the case that it lies above if more efficient regions exist outside the sample data. The theoretical bias is evident since $(x, y) \subseteq (X, Y)$, implying that the estimated production set $\hat{\psi}$ is a subset of Ψ, $\hat{\psi} \subseteq \psi$. Hence by definition, the estimator is upward biased, $\hat{\lambda} \geq \lambda$, where λ denotes the "true" efficiency scores.

Third, the asymptotic sampling distribution of the DEA estimator is generally very hard to derive. This is of importance, since the sampling distribution is needed in order to conduct inference on the estimated scores. It may therefore be difficult to attach any measure of uncertainty, such as standard errors and confidence intervals, to the estimated efficiency scores.

GIJBELS et al. (1999) derived the asymptotic sampling distribution in the most general setting with one input and one output vector, while KNEIP et al. (2003) did so in a multivariate setting. KNEIP et al. (2003) also showed that no closed form was available for the limiting distribution, and that closed form expressions for the moments and quantiles were impossible to obtain. Hence, standard analytical tools cannot be used to construct confidence intervals in the multivariate setting.

2.3. Bootstrapping DEA

SIMAR and WILSON (1998, 2000) introduced bootstrap methods in order to approximate the sampling distribution, and proposed using kernel density estimation, together with the reflection method (SILVERMAN: 1986) in a Monte Carlo setting, to estimate the bias and construct confidence intervals. More precisely, SIMAR and WILSON (1998, 2000) proposed drawing randomly from the truncated probability density function of the estimated efficiency scores, $\hat{\lambda}$, yielding a sampling distribution, denoted by $\hat{\psi}^* = \{(x_i^{\ b}, y_i^{\ b}); i = 1,...,n; b = 1,...,B\}$, where B is the total number of bootstrap replications, and n denotes the number of observations in the sample. The bootstrap method is asymptotically efficient since the approximation error due to the bootstrap resampling tends to zero, as $B \rightarrow \infty$, given n sufficiently large.

We use the smooth homogeneous bootstrap approach (See SIMAR and WILSON: 1998, 2006, for a detailed discussion). In addition to the usual, above-mentioned DEA assumptions concerning the data generating process, the procedure imposes the restriction that the distribution of the efficiency score is homogeneous over the input-output space. This implies that the distribution of the efficiency scores is unconditional upon the data, which SIMAR and WILSON (2006) argue is a valid assumption in many empirical situations. Moreover, the procedure involves solving *n(1+B)* linear programming problems.

SIMAR and WILSON (2006) provide simulation evidence that the smooth bootstrap DEA estimator works well in a setting of one input and one output. They also show that the performance of the estimator improves as the sample size increases.

The standard bootstrap approach imposes the restriction that all observations are drawn with equal probability, hence implying that the disturbances attached to each observation are i.i.d. drawings from the empirical distribution (See BIEWEN: 2001 for a comprehensive discussion). As pointed out by LÓPEZ-BAZO et al. (1999) and LÓPEZ-BAZO et al. (2004), this assumption may not be justified in the context of using country-specific panel data, since there are strong reasons to believe that the measurement disturbances due to the inherent bias of the original DEA estimator are spatially auto-correlated, i.e. country-specific. To control for this possible deficiency we also extend the bootstrap procedure by following BRÜLHART and TRAEGER (2005) and drawing blocks, where each block corresponds to regions belonging to the same host country. More precisely, for each replication, a sample is drawn randomly with equal probability among the total K blocks of the data.

When using the smooth homogeneous bootstrap procedure there are some practical considerations, the most important of which involves choosing a bandwidth for the kernel. Following HENDERSON and ZELENYUK (2007), we employ the method proposed by SHEATER and JONES (1991). This plug-in method is statistically optimal in the sense of minimizing the mean squared error of an estimator in a non-parametric model. Moreover, using a large-scale Monte Carlo experiment by JONES et al. (1996), it is shown to perform very well in small samples (See also PARK and TURLOCH: 1992)[1]. There are some theoretical advantages of using plug-in methods such as the SHEATER and JONES (1991)-method compared to using other methods, see JONES et al. (1996). The main theoretical advantage is that the rate of convergence towards the optimal bandwidth value is higher for the SHEATER and JONES (1991)- method than for other methods.

Secondly, the simulations are based on the Gaussian kernel. The choice of kernel has been shown to be of minor importance for the results (See SILVERMAN: 1986).

3. Data

DEA requires data on regional inputs (capital and labour) and outputs (measured as gross value added, GVA, at market prices). Data on regional output and labour is taken from the Cambridge Econometrics Data Set. All data is presented in the 1995 PPS obtained from Cambridge Econometrics. We have estimated capital stocks using the perpetual inventory method (PIM) from yearly regional investment series, since coherent regional capital stocks are currently unavailable. The investment series are from Cambridge Econometrics and start with 1980. Since we do not have access to sufficiently long regional investment series, we have built on earlier research in obtaining an initial estimate of the regional capital stock from which we have accumulated the depreciated investments (PACI and PUSCEDDU: 2000, MARROCU et al.: 2000, STEPHAN: 2000, MAS et al.: 2000, PRUD'HOMME: 1996). All stocks have been benchmarked to standardized estimates of the national capital stock (KAMPS: 2005, 2006) in order to avoid any systematic biases in the level of the regional stocks due to differing national assumptions about average service lives or depreciation patterns. Further description of the capital stocks may be found in Appendix A.

We use regional data from 69 regions for five different countries. Since the construction of regional capital stocks requires an estimate of the initial regional capital stock, we restrict our sample on the basis of data availability. The European countries for which we have been able to obtain initial estimates of regional capital stock are France, Italy, Spain, Germany and Ireland. That being said, we believe that this sample is representative of regions from different countries at various stages of joining and belonging to the European Union. We also believe that there is a definite merit in employing DEA in the largest possible sample of regions for which data has been obtained.

The regional disaggregation follows Eurostat's NUTS-classification system and all regions are measured at NUTS-level 2 apart from regions in Germany and Ireland, which are measured at NUTS-level 1. Studies on European regional disparities most commonly measure their variables at the geographical unit NUTS-level 2 (e.g. GARDINER et al. 2004, EZCURRA et. al 2005, CUADRO-ROURA et al. 2000). However, due to limited data on the regional capital stock we have had to include the German regions and Ireland measured at NUTS-level 1 (corresponding to measuring Germany at the Bundesländer level and Ireland at the national level). Naturally, as pointed out by CHESHIRE and MAGRINI (2000, pp. 457-458), the use of the NUTS-nomenclature in economic growth studies does not always correspond to economically functional regions. This problem is of utmost importance when comparing regional income disparities in cases where there is substantial commuting across regional borders, since GVA is generally collected on a workplace-basis but population number come from residential records. However, we focus on labour productivity disparities, thus measuring GVA and employment at the workplace, and therefore do not believe that this problem will affect our results. Our results may, however, be sensitive to the regional disaggregation chosen, especially since limited data availability forces us to measure Germany and Ireland at NUTS-level 1. In order to check how robust the shape of the regional distribution of labour productivity is to the differing NUTS-levels, we include the German and Irish regions at NUTS-level 2 (thus increasing the sample size from 69 to 92 regions).

However, this change of measure hardly alters the kernel density estimate of regional labour productivity[2].

4. Results

4.1. Intertemporal construction of the production frontier

Following HENDERSON and RUSSELL (2005) we compare the regional efficiency levels at the end points of our sample period, spanning 23 years from 1980 to 2002 by using intertemporal DEA. This means exploiting the panel nature of our data set by including all historical data up to the sample end when constructing the frontier for 2002. Note that we use the first 69 cross-sectional observations when constructing the production frontier for 1980, but 69×23=1587 panel observations for the construction of the production frontier in 2002. The advantage of calculating the production frontier in this intertemporal way is first of all that "technical regress" is ruled out, since the sequential construction of the frontier does not let it shift inward. Secondly, the construction follows the ABRAMOWITZ (1986) definition of catching-up, as latecomers are able to catch-up with the historical technological leaders by imitating their technology and thereby improving their own efficiency.

4.2. Bias-corrected technological frontiers

Figure 1 compares the originally estimated frontiers to the bootstrapped ones. The lower graph represents attainable output levels in 1980 whereas the higher one represents 2002. In both years the vast majority of regions are redundant in the construction of the frontier, since another region, or a linear combination of two regions could produce more output with the same use of inputs.

FIGURE 1 ABOUT HERE

As seen from the figure, both frontiers are biased downwards before the correction. The technological frontier shifts outwards at all capital per worker levels between 1980 and 2002. However, it shifts the most at high capital per worker ratios, implying that capital-intensive regions foremost benefited from technical change (i.e. not implying Hicks-neutral technical change). All frontiers have been calculated assuming constant returns to scale[3], and for each bootstrap exercise we have performed $B = 2000$ replications.

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4.3. Efficiency scores and confidence intervals

In order to measure the relative inefficiency of the dominated regions, we use the Farrell output-based efficiency index (FARRELL: 1957), which measures the distance from a region's actual observed output to the constructed frontier (its potential output). The index takes the value of one if the region is part of the constructed frontier in the evaluated period; for all other regions the efficiency index is less than one. Since the estimated frontier is biased downwards, the bias-corrected estimates are all less than one. The original and bias-corrected efficiency indices for the 69 regions calculated under the assumption of constant returns to scale in 1980 and 2002 are shown in table 1. The fourth and eighth column in the table indicate how many positions the region moves up or down in the internal relative efficiency ranking when calculated using the bootstrap method compared to the ordinary way.

TABLE 1 ABOUT HERE

Table 1 show that all efficiency estimates are biased upwards, but that the ranking of regions according to efficiency remains relatively stable even after the bias-correction. In 1980 the estimated bias is somewhat larger since the data set only consists of 69 observations, and consequently there is a little more turbulence in the relative ranking of regions according to efficiency. However, the relative position of most regions only changes one or two positions up or down the regional hierarchy in both 1980 and 2002, so we conclude that the bias-correction only changes the levels of the efficiency indices, not their internal distribution.

Figures 2 and 3 show the bias-corrected efficiency scores for all regions, together with accompanying confidence intervals, for 1980 and 2002 respectively.

FIGURE 2 ABOUT HERE

FIGURE 3 ABOUT HERE

In the 2002-sample we see how the regions that constitute the frontier (Ireland and Ile de France) are significantly more efficient than all other regions in the sample, except for Hamburg. In the 1980-sample, confidence intervals for the most efficient regions seem to overlap somewhat. However, the DEA methodology can successfully distinguish between technological leaders on the frontier and most other regions that are less efficient, especially when the sample size increases.

As pointed out in section 2.3, the standard bootstrapping procedure outlined above assumes that the disturbances attached to each observation are drawn with equal probability, although there might be reason to believe that measurement errors are country-specific. To control for this possible spatial autocorrelation we bootstrap the efficiency scores by drawing blocks of observations from the dataset, so that each block corresponds to regions from the same country. The last two rows in table 1 compare the average efficiency scores in 1980 and 2002 estimated using ordinary DEA, bias-corrected DEA estimates using the standard bootstrap procedure and the bias-corrected estimates from the block wise bootstrapping procedure. As seen from the table, the difference between the bias-corrected scores obtained from the two different bootstrapping procedures is minimal. The largest difference in bias-corrected efficiency scores and confidence intervals for any region in our sample is less than 1 percent after we correct for possible spatial autocorrelation[4].

Taken together, we find that the DEA methodology yields stable results with respect to the internal ranking of the regions after the bias-correction, and that the method successfully distinguishes the regions on the production frontier that are significantly more efficient than the other regions in the sample. We also find that the block wise bootstrapped efficiency scores are largely the same as those calculated using the original bootstrap. We therefore proceed by using the bias-corrected efficiency scores to decompose the factors of growth and relate these findings to the issue of labour productivity convergence since 1980.

4.4. Factors behind labour productivity growth

In order to analyze the factors affecting productivity growth in a certain region we use a decomposition of labour productivity growth into efficiency change (change of the obtained efficiency scores), technological change (shifts in the estimated production frontier) and capital accumulation (movements along the estimated production frontier) suggested by KUMAR and RUSSELL (2002: pp. 534-535). We regard shifts in the frontier as an indication of expanded technological opportunities[5], given that technology is publicly available, at every region’s respective capital per worker level. Changes in efficiency indicate the regions' relative catching-up or falling behind, given the available technology at their capital per worker ratios. Capital accumulation is simply measured as the movement along the estimated production frontier.

The decomposition is based on the bias-corrected efficiency indices in table 1 and exploits the assumption of constant returns to scale. We use the bias-corrected efficiency indices to obtain potential output per worker in the two periods as $\bar{y}_{1980}(k_{1980}) = y_{1980} / e_{1980}$ and $\bar{y}_{2002}(k_{2002}) = y_{2002} / e_{2002}$ and write labour productivity growth between 1980 and 2002 as:

$$\frac{y_{2002}}{y_{1980}} = \frac{e_{2002} \times \bar{y}_{2002}(k_{2002})}{e_{1980} \times \bar{y}_{2002}(k_{1980})}.$$

The potential output per worker at the 2002 capital per worker ratio using the existing technology in 1980 is, $\bar{y}_{1980}(k_{2002})$, and multiplying both numerator and denominator with this ratio gives:

$$\frac{y_{2002}}{y_{1980}} = \frac{e_{2002}}{e_{1980}} \times \frac{\bar{y}_{2002}(k_{2002})}{\bar{y}_{1980}(k_{2002})} \times \frac{\bar{y}_{1980}(k_{2002})}{\bar{y}_{1980}(k_{1980})}.$$

The first term on the right hand measures the relative contribution of relative efficiency changes (a movement towards or away from the frontier) to labour productivity growth in the region. The second term measures the effects of shifts in the frontier at the capital per worker levels for 2002 (which can be thought of as new or improved technology, since it expands the potential output for any given level of capital per worker). The third term measures changes in the capital per worker ratio (movements along the frontier at 1980's technology).

However, the separation of capital accumulation and technical change is not path-independent unless technology is independent of the capital to labour ratio (i.e. Hicks neutral). This means that measuring shifts in the frontier at the capital per worker ratio in 1980 and in 2002 will yield different results[6].

In order to avoid this arbitrariness, we have carried out the decomposition at capital per worker for both 1980 and 2002. When measuring technical change at capital per worker for 1980, capital accumulation is given relatively more importance than when the decomposition is carried out at the capital per worker for 2002. This is due to the fact that the shifts in the technological frontier are more prominent at high than at low capital per worker levels from 1980 onwards. In table 2 the decomposed indices are shown as the geometric averages of the two decompositions.

TABLE 2 ABOUT HERE

From the last row in table 2 we see that the average labour productivity growth between 1980 and 2002 is 40 percent. However, efficiency increases could not have contributed at all to these average productivity increases as most regions were falling behind the estimated frontier. Of the 69 regions, only eight actually show an increase in relative efficiency. Instead, increased technical opportunities and capital accumulation seem to have accounted for all of the observed average increases in labour productivity.

4.5. Relative contributions to β-convergence in labour productivity

In order to explore the relative contributions of our three decomposed sources of labour productivity growth to regional convergence, we have regressed the various indices upon initial labour productivity in 1980. Table 3 summarizes the regression coefficients and the Spearman rank correlation tests under the null hypothesis of no systematic relationship between both initial labour productivity in 1980 and labour productivity growth on the one hand and its decomposed sources on the other hand. The first row in the first column reveal that the regression coefficient between labour productivity in 1980 and labour productivity growth 1980-2002 is negative and statistically significant, which is an indication of unconditional β-convergence in this period. Nonetheless, the slope of the regression line is quite flat, showing that the process has been slow since 1980[7]. The Spearman's rank correlation in the second column also shows a statistically significant negative relationship between the two variables. Figure 4 confirms the unconditional β-convergence picture although the region with the highest labour productivity in 1980, Ile de France, has experienced the third highest labour productivity growth since 1980, only outperformed by Ireland and Extremadura. Thus, although there is a general negative correlation between initial productivity and productivity growth, the cases of Ile de France and, to some extent, Hamburg demonstrate that the convergence process has not been unambiguous.

FIGURE 4 ABOUT HERE

However, although there is statistical evidence of unconditional β-convergence, none of these growth effects seem to come from efficiency increases as the β-coefficient between labour productivity in 1980 and efficiency changes in the second row of table 3 is insignificant. This is consistent with the earlier conclusion that most regions were falling behind the productivity frontier, regardless of initial labour productivity. Again, Ireland is the only positive outlier.

The third row in table 3 suggests a negative relationship between initial labour productivity and the technological opportunities created when the production frontier shifts outward. In the context of the method, the remarkable example set by Ireland creates potential for technological improvements in low productivity regions. Although Ireland has shifted the frontier outwards at medium capital per worker levels, this "forging ahead" simultaneously implies that many low-productivity regions have fallen behind this frontier relatively. This result is different from earlier cross-country DEA studies in which technological change has been found to be Hicks non-neutral, benefiting countries with high capital per worker levels more than countries with little capital per worker (see for example KUMAR and RUSSELL:2002 and LOS and TIMMER: 2005). In our sample we do not find such clear evidence of non-neutrality, but the Western European sample does not include regions with such low capital per worker ratios as included in the above-mentioned studies. The example set by Ireland rather involves an expansion of the production possibility frontier for regions at modest capital per worker levels and explains why the technical contribution to growth is positive for these regions.

The last row in table 3 shows that capital accumulation has a dispersed effect on labour productivity growth, since the correlation is positive. This finding contradicts traditional neoclassical growth theory (SOLOW: 1957), in which capital accumulation is the force that drives convergence. It also shows that the efforts made by the European Union to support initial capital accumulation in unproductive regions have not generally been driving convergence. There are a few outliers, though notably Ireland, Auvergne and Galicia, for which capital accumulation has played a large role in labour productivity growth even though they had low labour productivity in 1980. At the same time, there have been large effects from capital accumulation in initially highly productive regions, like Ile de France, Hamburg and Lombardy, suggesting the presence of agglomeration forces in regions with the highest initial productivity in 1980.

4.6. Relative contributions to σ-convergence in labour productivity

Since the appropriateness of the concept of β-convergence has been criticised by e.g. QUAH (1993), we also relate the three decomposed sources of labour productivity growth to the evolution of the entire distributions of regional productivity for 1980 and 2002, a concept related to σ-convergence. The upper left panel in figure 5 displays the labour productivity distributions measured as kernel density diagrams in 1980 and 2002[8]. As seen from the figures, the two distributions are quite similar, but the 2002 distribution shows a higher mean., Since we are interested in finding out how the decomposed sources of growth affected the shape of the labour productivity distribution between 1980 and 2002 we follow KUMAR and RUSSELL (2002) and successively reconstruct the labour productivity distribution in 2002 by multiplying the 1980 distribution with the decomposed three factors as:

$$y_{2002} = (EFF \times TECH \times KACC)\, y_{1980}.$$

This reconstruction allows us to isolate the changes coming from one single source of growth in the entire productivity distribution by creating counterfactual variables. For example,

Deleted: ¶

$$y^{Eff}{}_{2002} = EFF \times y_{1980}$$

is a counterfactual variable that describes the productivity distribution in 2002, incorporating the effects from changes in efficiency only (assuming neither technological change nor capital accumulation). We have calculated similar counterfactual variables to single out the effects of technical change and capital accumulation on the distribution.

FIGURE 5 ABOUT HERE

The upper right panel in figure 5 shows the counterfactual variable measuring the effects of efficiency and the actual 2002 labour productivity distribution. The picture confirms that efficiency changes have been negative since 1980. In the absence of capital accumulation and technical change the 2002 regional productivity distribution would actually have been lower than in 1980.

In order to test whether the counterfactual variable is statistically significantly different from the actual variable in 2002 we use the non-parametric test for the comparison of two unknown distributions proposed by LI (1996) and FAN and ULLAH (1999)[9]. The null hypothesis of the test is H_0: $f(x)=g(x)$ for all x against the alternative, H_1: $f(x)\neq g(x)$ for some x. The results of the tests are given in table 4. The first row in the table confirms that the labour productivity distribution in 1980 is significantly different from the distribution in 2002 at the 5 percent level. In the second row we test whether the distributions remain significantly different after multiplying the 1980-distribution with the effects of efficiency changes. The Li-test is still rejected, which confirms that efficiency changes alone cannot account for the shift in the labour productivity distribution in 2002. This is consistent with our earlier result of a general pattern of falling behind between 1980 and 2002.

TABLE 4 ABOUT HERE

Earlier in this section we argued that the effect of technological change benefited the initially least productive regions relatively more and that technical change was a strong driving force in labour productivity growth. This is further emphasised by the kernels in the lower left panel in figure 5. The panel shows that isolating the technological effects makes the variable almost coincide with the actual 2002 variable. Whereas the actual labour productivity distribution displays a second bump in which a few very productive regions are clustered in 2002, the counterfactual variable is more uniform and has a higher mode. This is consistent with the earlier finding that technological change has raised the opportunity for convergence in the least productive regions. As seen in the third row in table 4, the counterfactual distribution singling out the effects of technological changes is still statistically significantly different from the actual labour productivity distribution in 2002. We interpret this as meaning that technological change has had a mean increasing effect on labour productivity but that it is not single-handedly responsible for the shape of the distribution in 2002.

The lower right panel in figure 5 shows that capital accumulation has had a diverging effect on the productivity distribution, since the counterfactual variable displays a lower mode and mean than the actual 2002 productivity distribution. This is again consistent with the earlier finding that capital accumulation has flowed to the most productive regions and that it has been a diverging force since 1980. In addition, the fourth row in table 4 shows that we cannot reject the null hypothesis at the 5 percent level (p-value 0.056) of the counterfactual productivity distribution coinciding with the actual productivity distribution in 2002. Although the p-value is still borderline significant, this can be taken as weak evidence that the capital accumulation variable drove most of the observed changes in the labour productivity distribution between 1980 and 2002. This is consistent with the earlier result that capital accumulation seems to have had a diverging effect on the labour productivity distribution. We have also added combinations of the decomposed scores in table 4, and find that we cannot reject similarity of the distributions in most cases when the decomposed sources of growth appear in pairs.

5. Conclusion

This paper employs a non-parametric frontier approach in combination with bootstrapping techniques in order to explore labour productivity growth in 69 Western European regions. We find that the relative ranking of efficiency scores obtained using DEA is stable with regard to bias-corrections, and that the estimated frontier consists of regions whose efficiency is significantly greater than the rest of the regions in the sample. In addition, we find that DEA is robust with regard to spatial autocorrelation, since block wise bootstrapping does not significantly change the bias-corrected estimates and confidence intervals.

The decomposition analysis shows that the economic hierarchy of the regions remained surprisingly stable over the investigated years, as only eight out of 69 regions improved their relative efficiency and caught up with the technological leaders. Instead, capital accumulation and expanded technological opportunities appear to explain all of the observed increases in labour productivity. Although the two forces have been of roughly equal importance in increasing the mean of the labour productivity distribution, technological change has created comparatively large opportunities for catching-up in initially low productive regions. However, these opportunities have not been realized and the low productive regions are therefore falling behind in relative efficiency.

Capital accumulation, on the other hand, has only played the expected converging role in initially unproductive regions. We find simultaneous evidence of agglomeration forces, since highly productive regions have also accumulated capital and thereby managed to increase labour productivity. Our results corroborate the earlier convergence literature in showing that the European convergence process has been slow and we find that capital accumulation plays a key role in understanding why initially productive regions have been forging ahead and why initially unproductive regions have not been catching up in absolute terms. This is similar to EZCURRA et al. (2005) who argue that the persistence of productivity inequalities is attributable to differences in the stock of physical capital and resources devoted to R&D. Understanding the role of capital accumulation in the European convergence process is a crucial step towards increasing our knowledge of the theoretical mechanisms behind regional growth, and may lead to important insights when formulating the EU's regional policy.

Appendix A. Construction of regional capital stocks

A 1. Establishing comparable national capital stocks as benchmarks

The lack of comparable capital stock data on the national level has received substantial attention recently. O'MAHONY (1996) shows for example that there are differences in assumptions about depreciation patterns and declining service lives in the national capital stocks reported by the official national statistical offices of the USA, the UK, Germany, France and Japan. The most important component of non-comparability in international capital stocks is, however, the differences in assumptions about the average service lives of the countries (O'MAHONY: 1996). In order to establish benchmarks for the capital stocks at the national level, we use a set of nationally comparable net capital stocks provided by KAMPS (2005, 2006). KAMPS employs the Perpetual Inventory Method (PIM) on investment series from 1860 to 2002 to construct a set of national net capital stocks that use the same time profile of depreciation.

A 2. Regional distribution of the national capital stocks

We construct regional capital stocks from regional investment series collected from Cambridge Econometrics from 1980 to 2002 using the Perpetual Inventory Method (PIM). The basic idea behind PIM is that the net capital stock in the beginning of the following period K_{t+1} may be expressed as:

$$K_{t+1} = K_t + I_t - d_t \times Kt$$

where I_t and d_t are gross investment and depreciation in the current period, respectively. Note that depreciation is expressed as a proportion of the net capital stock in the current year. Since our investment series start with 1980 we rely on various data sources explained in detail in the text below to obtain an estimate of the initial capital stock at year *t*. We also need an assumption concerning the depreciation rate, d_t. Once the regional capital stocks have been constructed, we calculate regional shares of the total net capital stock and thereafter these regional shares are multiplied with the national net capital stocks reported by KAMPS (2005, 2006). This means that the regional stocks are internationally comparable and benchmarked at the national level. The shares of the regional stock of total capital stock are also reasonably insensitive to the depreciation pattern used, which is what matters for the present study. We have chosen the depreciation rate in order to minimize the difference between the sum of the regional stocks and the total internationally comparably estimated capital stock. The depreciation rate that best corresponds to this criterion is usually around 4 percent annually.

Germany: From 1991 and onwards regional capital stock series have been reported by the Statistiches Landesamt Baden-Wurtemberg (www.statistik.baden-wuerttemberg.de) and the regional shares of the capital stocks are readily available to be apportioned to the national net capital stock provided by KAMPS. For the period 1980-1991, STEPHAN (2000) has estimated regional capital stocks using PIM on regional investment data. The regional shares from STEPHAN's data have been linked with the official regional shares for the overlapping year 1991 in order to obtain estimates of the regional shares for 1980 to 2002.

Italy: Regional Italian gross capital stocks, estimated at the sectorial level, are provided by CRENoS data bank at the University of Cagliari for 1970-1994, (www.crenos.it). The capital stocks of CRENoS data bank build on official investments series from ISTAT, Statistiche delle opere pubbliche. The regional capital stocks from 1980 and 1994 have been taken from CRENoS and the series have been extended using regional investments from Cambridge Econometrics and 4% depreciation.

Spain: Total capital stocks at the regional level have been obtained from Fundaciòn BBVA (www.fbbva.es) for the period 1964-1998. The stocks have been extended for 1998 to 2002 using 3.8 % linear depreciation and investment figures from Cambridge Econometrics.

France: Private regional capital stocks for industry and services were estimated for the years 1985-1992 by PRUD'HOMME (1996) using local tax data that indicates an unbiased interregional distribution of the private capital stock, which is what matters for the purpose of this paper. Data for the agricultural sector has been obtained from the Eurostat regional accounts where the measure of fixed capital consumption per year and region has been assumed to be in proportion to the regional agricultural stock of capital. In order to arrive at an estimate of the share of agriculture of the total French capital stock, data on net capital stock has been used from OECD STAN. The agricultural capital stock is about 3 percent of the total French capital stock.

Public capital stocks are harder to come by and therefore detailed investment series in transport and infrastructure, per asset from 1975 and onwards have been used to proxy the regional share of public capital stock. The infrastructure investment series come from Federation Nationale des Traveaux Publics (FNTP) and have been kindly provided by Andreas Stephan and Rémy Prud'Homme. On average the French public capital stock amounted to 17-18 % of the total capital stock during 1980-2002, so in the absence of better data, the cumulated sum of depreciated infrastructure investment proxies for the regional share of public capital of the total public capital stock. The investments have been depreciated linearly at 4 %. In order to arrive at estimates for the total regional capital stock, the sum of the private service and industry, agricultural and public capital stock for each region in 1992 is used as a benchmark and thereafter capital stock series are calculated forward and backward using regional investment data from Cambridge Econometrics and a 4 percent linear depreciation.

Ireland: For Ireland we employ the national net capital stocks reported by KAMPS (2005, 2006).

Appendix B. A non-parametric test for the difference between two unknown distributions

All distributions in the paper are kernel-based estimates of unknown density functions, $f(x)$, where x denotes a vector of dimension n of random variables, defined as:

$$f(x) = \frac{1}{nh}\sum_{j=1}^{n} k\left(\frac{x_j - x}{h}\right),$$

where the kernel density f satisfies all standard properties, see PAGAN and ULLAH (1999) and SILVERMAN (1986). The optimal bandwidth is denoted by h and estimated using the plug-in method proposed by SHEATER and JONES (1991). We assume that the kernel k is a symmetric standard normal density function with non-negative images.

We follow KUMAR and RUSSELL (2002) and use the method proposed by LI (1996) to test for the difference between two unknown distributions. The test statistic, T is defined as:

$$T = \frac{nh^{0.5} I}{\sigma},$$

shown by FAN and ULLAH (1999) to be asymptotically standard normally distributed. The variance σ^2 and the scalar I are calculated as:

$$I = \frac{1}{n^2 h} \sum_{i=1}^{n} \sum_{\substack{j=1 \\ i \neq j}}^{n} \left[k\left(\frac{x_i - x_j}{h}\right) + k\left(\frac{y_i - y_j}{h}\right) - k\left(\frac{y_i - x_j}{h}\right) - k\left(\frac{x_i - y_j}{h}\right) \right]$$

$$\sigma^2 = \frac{1}{n^2 h \pi^{0.5}} \sum_{i=1}^{n} \sum_{j=1}^{n} \left[k\left(\frac{x_i - x_j}{h}\right) + k\left(\frac{y_i - y_j}{h}\right) + 2k\left(\frac{y_i - x_j}{h}\right) \right].$$

In order to estimate the confidence intervals and the standard errors of the test statistic, we employ a bootstrap approximation, see LI and RACINE (2007), also implemented by KUMAR and RUSSELL (2002). We set the number of bootstrap replications to 1000 and calculate the critical values for the statistic at the 5 % significance level.

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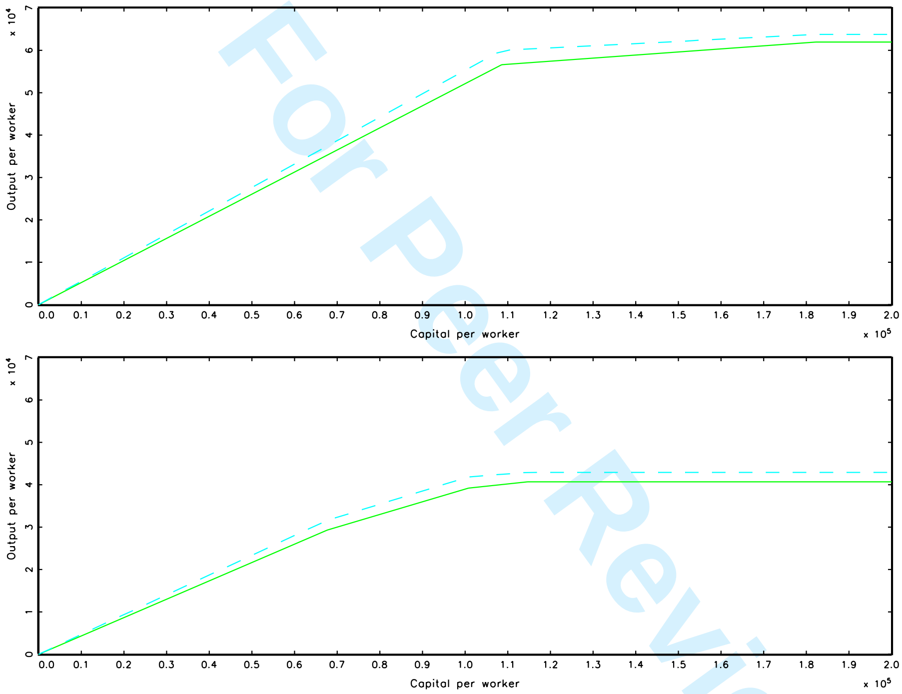
Figure 1. The constructed and bias-corrected technological frontiers in 1980 (below) and 2002 (above):



** Note that dotted lines refer to the bias-corrected frontiers*

Figure 2. Efficiency levels and confidence intervals for all regions in 1980:

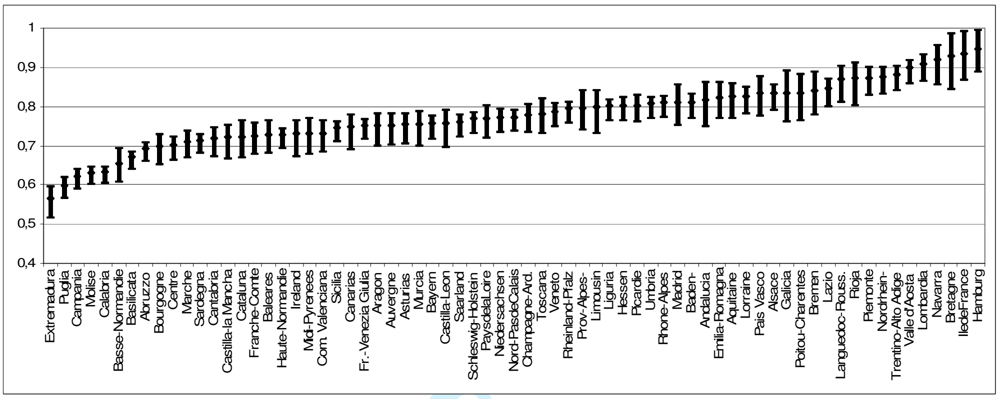


Figure 3. Efficiency levels and confidence intervals for all regions in 2002:

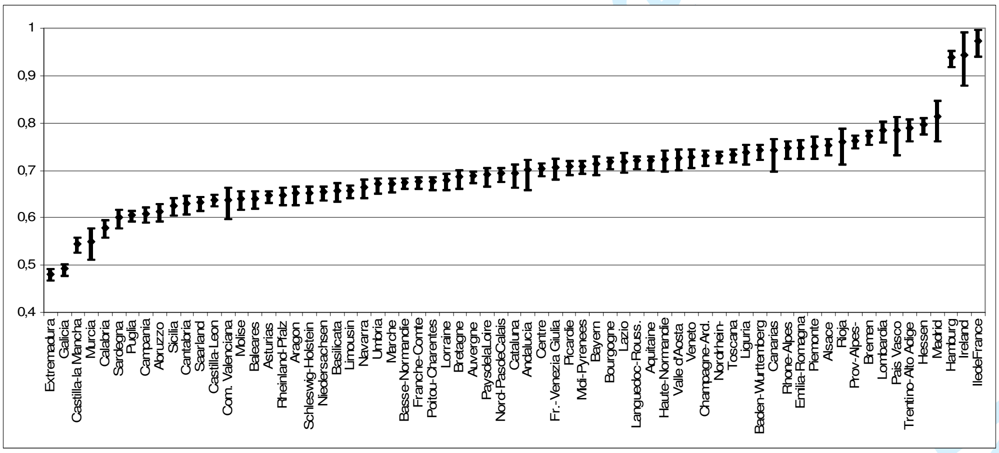


Figure 4. Labour productivity in 1980 (x-axis) versus labour productivity growth 1980-2002 (y-axis):

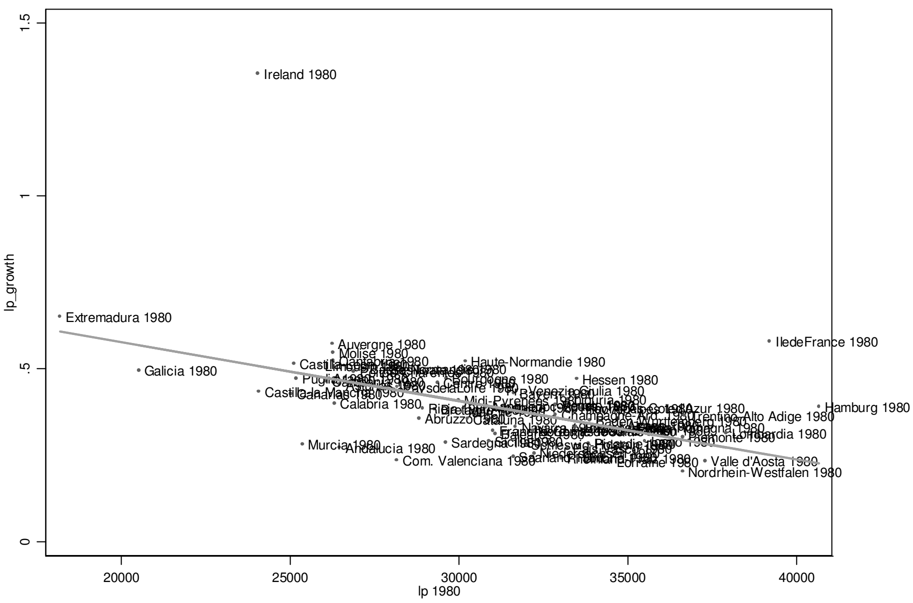


Figure 5. Counterfactual kernel distributions of labour productivity:

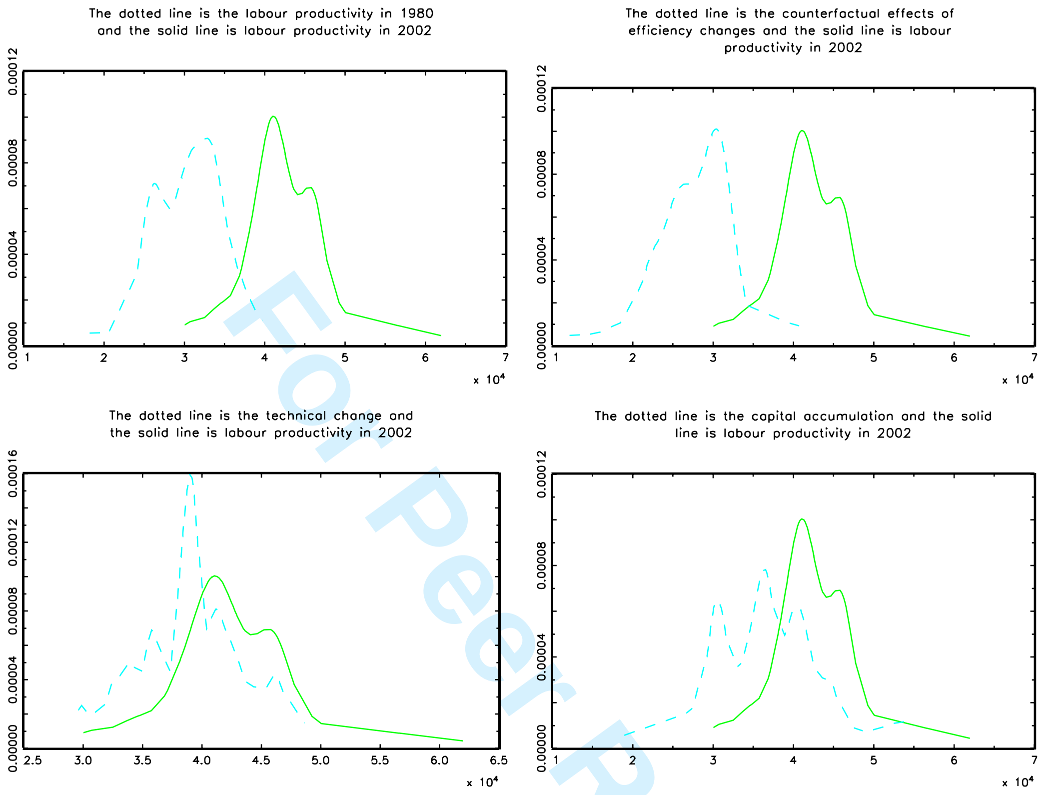


Table 1: Efficiency scores and bias corrections:

Region	Eff. 1980	Bias Corr.	d ranking	Region	Eff. 2002	Bias Corr.	d ranking
Hamburg	1.00	0.95	1	IledeFrance	1.00	0.97	0
IledeFrance	1.00	0.94	-1	Ireland	1.00	0.94	0
Bretagne	1.00	0.93	0	Hamburg	0.95	0.94	0
Navarra	0.96	0.92	0	Madrid	0.85	0.82	0
Lombardia	0.93	0.91	0	Hessen	0.81	0.80	1
Valle d'Aosta	0.92	0.90	0	Trentino-Alto Adige	0.81	0.79	1
Trentino-Alto Adige	0.90	0.88	2	Pais Vasco	0.81	0.78	-2
Nordrhein-Westfalen	0.90	0.88	3	Lombardia	0.81	0.78	0
Piemonte	0.90	0.87	1	Bremen	0.78	0.77	1
Rioja	0.91	0.87	-3	Prov-Alpes-Coted'Azur	0.77	0.76	1
Languedoc-Rouss.	0.91	0.87	-3	Rioja	0.79	0.76	-2
Lazio	0.87	0.84	4	Alsace	0.77	0.75	1
Bremen	0.90	0.84	0	Piemonte	0.77	0.75	-1
Poitou-Charentes	0.89	0.83	0	Emilia-Romagna	0.76	0.75	1
Galicia	0.90	0.83	-3	Rhone-Alpes	0.76	0.75	1
Alsace	0.86	0.83	5	Canarias	0.77	0.74	-2
Pais Vasco	0.88	0.83	-2	Baden-Wurttemberg	0.75	0.74	1
Lorraine	0.85	0.83	4	Liguria	0.76	0.74	-1
Aquitaine	0.86	0.82	0	Toscana	0.74	0.73	1
Emilia-Romagna	0.87	0.82	-3	Nordrhein-Westfalen	0.74	0.73	5
Andalucia	0.87	0.82	-3	Champagne-Ard.	0.74	0.73	2
Baden-Wurttemberg	0.83	0.81	3	Veneto	0.75	0.73	-3
Madrid	0.86	0.81	-3	Valle d'Aosta	0.74	0.73	-2
Rhone-Alpes	0.83	0.81	3	Haute-Normandie	0.74	0.72	-2
Umbria	0.82	0.81	3	Aquitaine	0.73	0.72	2
Picardie	0.83	0.80	0	Languedoc-Rouss.	0.73	0.72	2
Hessen	0.82	0.80	2	Lazio	0.74	0.72	-3
Liguria	0.82	0.80	3	Bourgogne	0.73	0.72	1
Limousin	0.84	0.80	-5	Bayern	0.73	0.71	-3
Prov-Alpes-Coted'Azur	0.85	0.80	-7	Midi-Pyrenees	0.72	0.71	2
Rheinland-Pfalz	0.81	0.80	1	Picardie	0.72	0.71	2
Veneto	0.81	0.79	2	Fr.-Venezia Giulia	0.72	0.71	-2
Toscana	0.82	0.78	-3	Centre	0.71	0.70	1
Champagne-Ard.	0.81	0.78	-1	Andalucia	0.72	0.70	-3
Nord-PasdeCalais	0.79	0.77	3	Cataluna	0.71	0.70	0
Niedersachsen	0.79	0.77	1	Nord-PasdeCalais	0.70	0.69	1
PaysdelaLoire	0.81	0.77	-2	PaysdelaLoire	0.70	0.69	-1
Schleswig-Holstein	0.79	0.77	3	Auvergne	0.70	0.69	1
Saarland	0.78	0.76	7	Bretagne	0.70	0.69	-1
Castilla-Leon	0.79	0.76	-4	Lorraine	0.69	0.68	0
Bayern	0.78	0.76	4	Poitou-Charentes	0.69	0.68	0
Murcia	0.79	0.76	-3	Franche-Comte	0.68	0.68	0
Asturias	0.79	0.75	-3	Basse-Normandie	0.68	0.67	1
Auvergne	0.79	0.75	-2	Marche	0.68	0.67	1
Aragon	0.78	0.75	-2	Umbria	0.68	0.67	-2
Fr.-Venezia Giulia	0.77	0.75	4	Navarra	0.68	0.66	0
Canarias	0.78	0.75	-3	Limousin	0.67	0.66	1

Sicilia	0.76	0.74	6	Basilicata	0.67	0.66	-1
Com. Valenciana	0.77	0.73	0	Niedersachsen	0.67	0.65	1
Midi-Pyrenees	0.78	0.73	-3	Schleswig-Holstein	0.67	0.65	-1
Ireland	0.77	0.73	1	Aragon	0.67	0.65	0
Haute-Normandie	0.74	0.73	5	Rheinland-Pfalz	0.66	0.65	0
Baleares	0.77	0.73	-2	Asturias	0.66	0.65	2
Franche-Comte	0.76	0.72	-1	Baleares	0.66	0.64	0
Cataluna	0.77	0.72	-7	Molise	0.66	0.64	1
Castilla-la Mancha	0.76	0.72	-1	Com. Valenciana	0.66	0.64	-3
Cantabria	0.75	0.72	-1	Castilla-Leon	0.65	0.64	0
Sardegna	0.73	0.71	2	Saarland	0.64	0.63	1
Marche	0.74	0.71	-1	Cantabria	0.65	0.63	-1
Centre	0.72	0.70	1	Sicilia	0.64	0.63	0
Bourgogne	0.74	0.70	-2	Abruzzo	0.63	0.61	0
Abruzzo	0.71	0.69	0	Campania	0.62	0.61	0
Basilicata	0.68	0.67	1	Puglia	0.61	0.61	1
Basse-Normandie	0.70	0.66	-1	Sardegna	0.62	0.60	-1
Calabria	0.65	0.63	0	Calabria	0.59	0.58	0
Molise	0.65	0.63	0	Murcia	0.58	0.55	0
Campania	0.64	0.62	0	Castilla-la Mancha	0.56	0.54	0
Puglia	0.62	0.60	0	Galicia	0.50	0.49	0
Extremadura	0.60	0.56	0	Extremadura	0.49	0.48	0
Average	0.809	0.777			0.713	0.697	
Average (block bootstrap)		0.781				0.699	

Table 2: Decomposition results:

Region	Y / L 1980	Y / L 2002	Prod. Growth	EFF	TECH	KACC
Abruzzo	28 822	39 119	0.36	-0.11	0.23	0.24
Alsace	34 813	46 546	0.34	-0.10	0.13	0.30
Andalucia	26 462	33 684	0.27	-0.14	0.32	0.12
Aquitaine	30 791	42 803	0.39	-0.13	0.33	0.20
Aragon	26 098	38 452	0.47	-0.13	0.32	0.29
Asturias	26 480	38 555	0.46	-0.14	0.50	0.13
Auvergne	26 246	41 289	0.57	-0.08	0.24	0.39
Baden-Wurttemberg	33 874	45 785	0.35	-0.08	0.37	0.08
Baleares	31 080	40 815	0.31	-0.12	0.27	0.18
Basilicata	27 813	41 685	0.50	-0.02	0.17	0.31
Basse-Normandie	27 192	40 843	0.50	0.03	0.25	0.17
Bayern	31 628	45 214	0.43	-0.06	0.20	0.27
Bourgogne	29 623	43 635	0.47	0.03	0.14	0.26
Bremen	34 959	46 255	0.32	-0.08	0.16	0.24
Bretagne	29 287	40 518	0.38	-0.26	0.54	0.21
Calabria	26 313	36 840	0.40	-0.09	0.34	0.14
Campania	26 067	38 181	0.46	-0.02	0.25	0.19
Canarias	25 027	35 735	0.43	-0.01	0.18	0.21
Cantabria	26 284	40 076	0.52	-0.12	0.47	0.18
Castilla-la Mancha	24 081	34 540	0.43	-0.25	0.75	0.08
Castilla-Leon	25 115	38 073	0.52	-0.16	0.49	0.21
Cataluna	30 252	41 006	0.36	-0.04	0.42	-0.01
Centre	29 373	42 881	0.46	0.01	0.23	0.18
Champagne-Ard.	32 864	44 982	0.37	-0.06	0.17	0.25
Com. Valenciana	28 164	34 807	0.24	-0.13	0.28	0.10
Emilia-Romagna	35 101	46 762	0.33	-0.09	0.23	0.19
Extremadura	18 190	30 031	0.65	-0.15	0.86	0.04
Fr.-Venezia Giulia	31 224	44 921	0.44	-0.06	0.23	0.25
Franche-Comte	31 020	41 002	0.32	-0.07	0.26	0.13
Galicia	20 528	30 718	0.50	-0.41	0.97	0.29
Hamburg	40 663	56 547	0.39	-0.01	0.04	0.35
Haute-Normandie	30 193	45 959	0.52	-0.01	0.18	0.30
Hessen	33 491	49 267	0.47	-0.01	0.17	0.26
IledeFrance	39 206	61 963	0.58	0.04	0.13	0.34
Ireland	24 049	56 603	1.35	0.29	0.24	0.47
Languedoc-Rouss.	30 823	42 955	0.39	-0.17	0.42	0.19
Lazio	35 516	45 846	0.29	-0.15	0.31	0.15
Liguria	33 228	46 958	0.41	-0.08	0.15	0.34
Limousin	25 869	39 045	0.51	-0.18	0.51	0.21
Lombardia	37 915	49 850	0.31	-0.14	0.12	0.36
Lorraine	34 511	42 530	0.23	-0.18	0.05	0.43
Madrid	33 938	44 962	0.32	0.01	-0.06	0.41
Marche	30 112	41 459	0.38	-0.05	0.30	0.12
Midi-Pyrenees	29 986	42 247	0.41	-0.03	0.31	0.11

Molise	26 274	40 656	0.55	0.01	0.28	0.19
Murcia	25 363	32 496	0.28	-0.27	0.53	0.16
Navarra	31 685	42 204	0.33	-0.28	0.46	0.26
Niedersachsen	32 226	40 492	0.26	-0.15	0.31	0.14
Nord-PasdeCalais	32 179	42 556	0.32	-0.10	0.19	0.24
Nordrhein-Westfalen	36 629	44 073	0.20	-0.17	0.21	0.19
Pais Vasco	33 211	42 201	0.27	-0.06	0.24	0.09
PaysdelaLoire	28 177	40 812	0.45	-0.10	0.32	0.22
Picardie	33 837	43 482	0.29	-0.12	0.27	0.15
Piemonte	36 630	47 754	0.30	-0.14	0.24	0.23
Poitou-Charentes	26 888	40 126	0.49	-0.19	0.82	0.01
Prov-Alpes-Coted'Azur	33 428	46 386	0.39	-0.04	0.13	0.27
Puglia	25 183	37 099	0.47	0.01	0.21	0.20
Rheinland-Pfalz	33 036	41 012	0.24	-0.19	0.23	0.24
Rhone-Alpes	33 585	46 583	0.39	-0.08	0.23	0.22
Rioja	28 929	40 115	0.39	-0.13	0.36	0.17
Saarland	31 615	39 401	0.25	-0.17	0.31	0.14
Sardegna	29 611	38 147	0.29	-0.16	0.22	0.26
Schleswig-Holstein	31 976	41 051	0.28	-0.15	0.23	0.23
Sicilia	30 892	39 870	0.29	-0.16	0.27	0.21
Toscana	33 485	44 647	0.33	-0.06	0.15	0.23
Trentino-Alto Adige	36 681	50 054	0.36	-0.11	0.25	0.22
Umbria	33 504	41 733	0.25	-0.17	0.23	0.22
Valle d'Aosta	37 286	46 035	0.23	-0.19	0.05	0.45
Veneto	32 866	45 929	0.40	-0.07	0.25	0.21
Average			0.40	-0.10	0.29	0.22

Table 3: Regression lines for Spearman's Rank correlation test (output per worker, 1980):

Dep. variable	Beta	Spearman
LP growth	-1.69e05 (0.0000)	-0.5562 (0.0000)
EFF	1.88e-06 (0.4830)	0.0314 (0.7979)
TECH	-2.80e-05 (0.0000)	-0.5782 (0.0000)
KACC	6.90e-06 (0.0100)	0.2974 (0.0131)

Note: p-values of the coefficients are given in the parenthesis.

Table 4: Distribution Hypothesis Test:

Null hypothesis	t-stat	p-value
f(y2002) = g(y1980)	1.7572	0.0394
f(y2002) = g(y1980*EFF)	1.9915	0.0232
f(y2002) = g(y1980*TECH)	1.8771	0.0302
f(y2002) = g(y1980*KACC)	1.5882	0.0562
f(y2002) = g(y1980*EFF*TECH)	1.4369	0.0754
f(y2002) = g(y1980*EFF*KACC)	1.6479	0.0495
f(y2002) = g(y1980* TECH*KACC)	1.4895	0.0681

[1] There are several different procedures for choosing the bandwidth (See JONES et al.: 1996 and LI and RACINE: 2007 for a detailed discussion). For instance, SIMAR and WILSON (2000, 2006) propose using the cross-validation method.

[2] The different kernel densities are available from the authors upon request.

[3] The distribution of efficiency scores is not very sensitive to the returns-to-scale assumption, although individual efficiency estimates may vary somewhat.

[4] The results of the block wise bootstrap are available from the authors upon request.

[5] Technology and efficiency are here defined in a very broad sense, since improved institutions or human capital may also increase regional output and thereby shifts or movements in the production frontier.

[6] It should be emphasized that the problem of path dependency is endemic to the task of measuring technical change, and most commonly solved by simply assuming Hick's neutrality. It was for example this assumption, in combination with constant returns to scale, that enabled SOLOW (1957) and the subsequent growth accounting school to unambiguously separate capital accumulation from TFP growth.

[7] It should be noted that the regressions in table 3 do not take into account that spatial autocorrelation may bias the results. We have tested the absence of residual spatial dependence with Moran's I (using a set of binary weights that take a value of 1 for regions that share a common border and 0 otherwise). Under the normality assumption and the null

hypothesis of no spatial autocorrelation we obtain a z-statistic of 12.5 for the first regression, which indicates the presence of positive and significant spatial autocorrelation in the residuals. However, as the tests in table 3 only should demonstrate the direction of correlation between two variables and are not intended to be full regression models from which convergence rates are estimated, we proceed our convergence analysis by studying the entire distribution of labour productivity as suggested in QUAH (1993).

[8] All Kernel diagrams are based on the Gaussian kernel and the bandwidth is obtained using SHEATER and JONES (1991) plug-in method, see Appendix B.

[9] The non-parametrical test is described in Appendix B.