Relative sources of European regional productivity convergence: A bootstrap frontier approach

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Relative sources of European regional productivity convergence: A bootstrap frontier approach*

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Abstract

We address the issue of Western European regional productivity growth and convergence by means of Data Envelopment Analysis (DEA), decomposing labor 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 a diverging effect on the labor productivity distribution. We also account for the inherent bias and the stochastic elements in the efficiency estimation using bootstrapping methods. We find that the relative ranking of the bias-corrected efficiency scores remains stable after the bias correction and that the DEA successfully identifies the regions on the production frontier as significantly more efficient than other regions.

JEL Classification: C14, C15, O47, R1

Keywords: Bootstrap, DEA, Efficiency, Regional Convergence

1 Introduction

The issue of regional convergence within the European Union has attracted 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 recent studies have also focused on labor productivity as a key factor behind regional growth. GARDINER et al. (2004), for example report that the degree of convergence in labor productivity has been disappointingly slow and that much of it seems to have taken place in the boom years of the 1980s.

Our study continues the analysis of productivity growth and convergence using Data Envelopment Analysis (DEA) in combination with a decomposition of labor productivity growth into three components:

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efficiency change, technical change and capital accumulation. We use a data set consisting of 69 Western European NUTS 2-regions from France, Germany, Italy, Spain and Ireland between 1980 and 2002 which means that we are able to address the proximate causes behind the slow regional convergence process across a larger sample of regions than what has previously been done using DEA. Earlier regional studies have mainly estimated efficiency and technical change for regions within one country, not across countries. Specifically, MAUDOS et al. (1998) 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 traditional growth accounting decomposition of technical change and factor accumulation yields biased results in the presence of inefficiency (GROSSKOPF: 1993). In addition, the 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 of 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 labor productivity growth into efficiency and technical change. Recent contributions include the incorporation of capital accumulation (KUMAR and RUSSELL: 2002) and human capital accumulation (HENDERSON and ZELENYUK: 2006) into the decomposition framework and the extension of relating the decomposed sources of labor productivity growth to the question of convergence (MAUDOS et al.: 2000, LOS and TIMMER: 2005).

With this growing interest in the DEA-approach to growth accounting there is an increasing need to deal with its major short-comings, 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 means of incorporating stochastic elements in the DEA. In contrast to previous studies, the use of bootstrapping methods allow us to gauge the relative sensitivity of the estimated efficiency scores to the inherent bias of the DEA. Specifically, we are interested in analyzing whether the regions' relative efficiency levels change after the bias-correction and whether the DEA is powerful enough to distinguish regions on the production frontier as significantly more efficient than the other regions in the sample.

Major findings are that the relative efficiency ranking of the regions remain stable after the bias correction and that the DEA successfully identifies regions on the production frontier as significantly more efficient than most other regions in the sample. We also investigate the proximate driving forces behind regional labor productivity growth by decomposing changes in labor productivity into the effects of technological change, efficiency increases and capital deepening and find that most regions have fallen behind the production frontier in efficiency. Moreover, capital accumulation has had a dispersed effect on the labor productivity distribution of the 69 regions since 1980.

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, while section 5 concludes the paper.

2 Methodology

2.1 The DEA

Assume that the production set Ψ is spanned by a set of input and output vectors. More formally, let $\Psi = \left\{(X, Y) \in \mathbb{R}^{N+M}\right\}$. 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 denotes 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 $\left\{\widehat{\lambda}_i = \widehat{\theta}_i^{-1}; i = 1, ..., n\right\}$ of the attainable set Ψ are defined as:

$$\widehat{\theta}_i\,(x_i, y_i) = \sup\left[\theta \mid (x_i, \theta y_i) \in \widehat{\Psi}\right];\ i = 1, ..., n,$$

where the subset $\widehat{\Psi}$ is spanned by the sample input and output vectors $\left\{\widehat{\Psi} = (x_i, y_i) \in \mathbb{R}^{N+M}; i = 1, ..., n\right\}$. SIMAR and WILSON (1998, 2000, 2006) show that $\widehat{\lambda}$ 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 Ψ are standard in microeconomic theory, for which we refer to FÄRE et al. (1994b) for a comprehensive discussion.

2.2 Deficiencies with the DEA

The DEA estimator suffer 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 practise observations in the sample. Although the procedure rules out the possibility that the "true" frontier lies below the constructed frontier, there might be the case that it lies above the constructed one, 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 $\widehat{\Psi}$ is a subset of Ψ, $\widehat{\Psi} \subseteq \Psi$. Hence by definition, the estimator is upward biased, $\widehat{\lambda} \geq \lambda$, 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. Therefore, it may be difficult to present some 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) derived the sampling distribution in a multivariate setting. However, the results of KNEIP et al. (2003) show that no closed form for the limiting distribution is available and that closed form expressions for the moments and quantiles are impossible to obtain. Hence, standard analytical tools cannot be used to construct confidence intervals in the multivariate setting.

2.3 Bootstrapping the DEA

SIMAR and WILSON (1998, 2000) introduced bootstrap methods in order to approximate the sampling distribution. These authors propose 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) propose to draw randomly from the truncated probability density function of the estimated efficiency scores $\widehat{\lambda}$, yielding a sampling distribution, denoted by $\widehat{\Psi^*} = \left\{\left(x_i^b, y_i^b\right);\ i = 1, ..., n;\ b = 1, ..., B\right\}$, 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 $B \to \infty$, 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 on 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, for which SIMAR and WILSON (2006) argues 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 the setting of one input and one output. They show that the performance of the estimator improves as the sample size increases.

There are some practical considerations when using the smooth homogeneous bootstrap procedure. The most important one involves choosing a bandwidth for the kernel. Following HENDERSON and ZELENYUK (2006), we employ the method proposed by SHEATER and JONES (1991). Secondly, the simulations are based on the gaussian kernel, although the choice of kernel has been shown to be of minor importance for the results (See SILVERMAN: 1986).

3 Data

The DEA requires data on regional inputs (capital and labor) and outputs (measured as gross value added, GVA, at market prices). Data on regional output and labor is taken from the Cambridge Econometrics Data Set. The regional disaggregation follows Eurostat's NUTS classification system and all regions are measured at NUTS-level 2 apart from Ireland and Germany, where the regions are measured at NUTS-level 1. All data is presented in 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 were obtained from the Cambridge Econometrics and start in 1980. Since we did 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 started to accumulate the depreciated investments (PACI and PUSCEDDU: 2000, MARROCU and PACI: 2000, STEPHAN: 2000, MAS, PEREZ and URIEL: 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 can be found in Appendix.

4 Results

4.1 Intertemporal construction of the production frontier

We compare the regional efficiency levels at the end points of our sample period, spanning over 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 until 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 $69 \times 23 = 1587$ panel observations for the construction of the production frontier in 2002[1]. 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 intertemporal construction rules out the possibility that short-term fluctuations in output affect the production possibility frontiers. Thirdly, the construction follows ABRAMOWITZ (1986) definition of catching-up, as latecomers are able to catch-up with the historical technological leaders by imitating their technology and thereby improve their own efficiency.

4.2 Bias-corrected technological frontiers

Figure 1 compares the originally estimated frontiers to the bootstrapped ones where the lower graph represents attainable output levels in 1980 whereas the higher one represents 2002. In both years the vast majority of regions were 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.

FIGURE1 ABOUT HERE

As seen from the figure, both frontiers were biased downwards before the correction. The figure also shows that the technological frontier has shifted outwards at all capital per worker levels between 1980 and 2002. However, the frontier shifted 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[2] and for each bootstrap exercise, we perform $B = 2000$ replications[3].

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). This index measures the distance from a region's actual observed output to the constructed frontier (its potential output). The index will take the value of one if the region is part of the constructed frontier at the evaluated period, for all other regions the efficiency index will be 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 presented in table 1. The fourth and eighth column in the table also present how many slots the region move up or down in the internal relative efficiency ranking when calculated the bootstrapped way compared to the ordinary way.

TABLE1 ABOUT HERE

Table 1 also shows 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 change one or two slots 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.

Figure 2 and 3 show all regions bias-corrected efficiency score with accompanying confidence intervals for 1980 and 2002 respectively.

FIGURE2 ABOUT HERE

FIGURE3 ABOUT HERE

The figures display that estimating the production frontier in an intertemporal way drastically increases the precision of the efficiency scores. In the 2002-sample we see how the regions consisting of 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 discriminates successfully between technological leaders on the frontier and most regions that are less efficient, especially when the sample size increases.

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 discriminates between the regions on the production frontier as significantly more efficient than the other regions in the sample. Therefore, we proceed by using the bias-corrected efficiency scores to decompose the factors of growth and relate these findings to the issue of labor productivity convergence since 1980.

4.4 Factors behind labor productivity growth

In order to analyze factors affecting productivity growth in a certain region, we use a decomposition of labor 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[4], available to adopt given that technology is publicly available, at every regions' respective capital per worker level. Changes in efficiency indicate the regions' relative catch-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 we presented 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 labor productivity growth between 1980 and 2002 as:

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

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 top and bottom with this ratio gives:

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

The first right-hand term measures the relative contribution of relative efficiency changes (a movement towards or away from the frontier) to labor 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 labor ratio (i.e. Hicks neutral). This means that measuring shifts in the frontier at the capital per worker ratio in 1980 or in 2002 will yield different results[5].

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

TABLE2 ABOUT HERE

From the bottom row in table 2 we find that the average labor productivity growth between 1980 and 2002 has been 40 percent. However, efficiency increases did not at all contribute to these average productivity increases, as most regions were falling behind the estimated frontier. Instead, increased technical opportunities and capital accumulation seem to have accounted for all of the observed average increases in labor productivity.

4.5 Relative contributions to labor productivity convergence

In order to explore the relative contributions of our three decomposed sources of labor productivity growth to regional convergence, we have plotted the various indices against initial labor productivity in 1980. Figure 4 confirms that there is a weak tendency for convergence in labor productivity among the 69 regions during the last two decades, since labor productivity in 1980 and labor productivity growth seem to be somewhat negatively related.

FIGURE4 ABOUT HERE

The prominent outlier at low labor productivity levels in 1980 refers to the Irish growth miracle, but apart from this region, the general tendency for convergence is quite weak, as some regions at initially high labor productivity levels also show generally high labor productivity increases. In addition, the region with the highest labor productivity in 1980, Ile de France, has experienced the third highest labor productivity growth since 1980, only outperformed by Ireland and Extremadura. Thus, although there is a slight 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.

The percentage changes in the efficiency indices plotted against initial labor productivity growth in figure 5 do not exhibit any general tendency.

FIGURE5 ABOUT HERE

Rather, the majority of regions have fallen behind the technological frontier, no matter their initial labor productivity. However, the largest fall in relative efficiency is found among regions with low to medium labor productivity in 1980, for example Bretagne, Castilla-la-Mancha, Murcia and Navarra. Out of the 69 regions, only eight actually show an increase in relative efficiency and again, Ireland is the only positive outlier. Thus, the general pattern seems to be one of "falling behind" between 1980 and 2002.

In figure 6 the relationship between initial labor productivity and the relative contribution of shifts in the production frontier is displayed.

FIGURE6 ABOUT HERE

The plot suggests a clear negative relationship between initial labor productivity and the technological opportunities created when the production frontier shifted outward. The large potential for technological improvements in low-productivity regions is due to the remarkable example set by Ireland at relatively modest capital per worker levels. Although Ireland has shifted the frontier outwards at medium capital per worker levels, this "forging ahead" simultaneously meant that many low-productivity regions have fallen behind this frontier relatively.

The plot of capital accumulation in figure 7 shows a dispersed effect of capital accumulation on labor productivity growth.

FIGURE7 ABOUT HERE

Capital accumulation has played a large role for labor productivity growth in initially low productivity regions, like Ireland, Auvergne or Galicia, indicating that capital may have been flowing to high marginal returns in relatively unproductive regions thereby causing labor productivity convergence. At the same time, there have been large effects from capital accumulation in initially highly productive regions, like Ile de France, Hamburg and Lombardia, suggesting forces of agglomeration in the regions that displayed the highest initial productivity in 1980.

5 Conclusion

This paper has employed a non-parametric frontier approach in combination with bootstrapping techniques in order to explore labor productivity growth in 69 Western European regions. We find that the relative ranking of efficiency scores obtained using DEA is stable to bias-corrections and that the estimated frontier consists of regions whose efficiency is significantly larger than the rest of the regions in the sample. Since the frontier is constructed intertemporally, the biases due to sample choice become very small in 2002 and confidence intervals indicate high precision of the DEA scores.

The decomposition analysis showed 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 labor productivity. Although the two forces have been of roughly equal importance in increasing the mean of the labor productivity distribution, technological change has created comparatively large opportunities for catching-up in initially low productive regions. However, this opportunity has not been realized and the low productive regions are therefore falling behind in relative efficiency.

Capital accumulation, on the other hand, has played the expected converging role in initially unproductive regions. However, we find simultaneous evidence of agglomeration forces, since highly productive regions have also accumulated capital and thereby managed to increase labor productivity. Understanding the role of capital accumulation for the European convergence process is a crucial step towards increased knowledge about the theoretical mechanisms behind regional growth and can lead to important insights when formulating the EU:s regional policy.

Notes

[1]There may be some autocorrelation pattern present in the data. However, this should not infer any estimation problems, since we use a large number of datapoints.

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

[3]Bootstrapping these frontiers is an extremely computing-intensive process, especially for the latter sample since bootstrapping the intertemporally constructed frontier for 2002 means solving 3175587 linear optimzation problems. This

simulation took about 150 hours on a pentium 4 to complete.

[4]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.

[5]It shall be emphasized that the problem of path dependency is endemic to the task of measuring technical change, and most commonly it has been 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.

Appendix. Construction of regional capital stocks

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) showed for example that there are differences in assumptions about depreciation patterns and declining service lives in the national capital stocks reported by official national statistical offices of USA, UK, Germany, France and Japan. The most important component of non-comparability in international capital stocks is however differences in assumptions about average service lives between 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 Perpetual Inventory Method (PIM) on investment series from 1860-2002 in order to construct a set of national net capital stocks that use the same time profile of depreciation.

Regional distribution of the national capital stocks

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

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

where I_t and d_t are gross investment and depreciation in the current period, respectively. Notice that depreciation is expressed as a proportion of the net capital stock in the current year. Since our investment series start in 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 of 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 share 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 to total capital stock are also reasonably insensitive to the depreciation pattern used, which is what matters for the present study. We chose 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 criteria 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 (2001) has estimated regional capital stocks using PIM on regional investment data. The regional shares from STEPHAN's data have been linked for the overlapping year 1991 with the official regional shares in order to obtain estimates of the regional shares from 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 between 1980 and 1994 were taken from CRENoS and thereafter the series were extended using regional investments from Cambridge Econometrics and 4% depreciation.

Spain: Total capital stocks at the regional level were obtained from Fundaciòn BBVA (www.fbbva.es) for the period 1964-1998. The stocks were 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 should indicate an unbiased interregional distribution of the private capital stock, which is what matters for the present purpose. Data for the agricultural sector was obtained from the Eurostat regional accounts where the measure of fixed capital consumption per year and region has been assumed to stand in proportion to the regional agricultural stock of capital. In order to arrive at an estimate of the share of agriculture to 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 was 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 absence of better data, the cumulated sum of depreciated infrastructure investment proxies for the regional share of public capital to the total public capital stock. The investments were 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 4 percent linear depreciation.

References

[1] CANALETA, C.G., ARZOZ, P.P. and GÁRATE, M.R. (2003) Productivity, Public Capital and Convergence: A Study of the Spanish Regions. *Tijdschrift voor Economische en Sociale Geografie,* 94:5, pp. 537-553.

[2] CORRADO L., MARTIN R. and WEEKS M. (2005) Identifying and Interpreting Regional Convergence Clusters across Europe, *Economic Journal*, 115(502), pp. 133-160.

[3] DEBREU, G. (1959) *Theory of Value*, Yale University Press.

[4] FAGERBERG J. and VERSPAGEN B. (1996) Heading for divergence? Regional growth in Europe reconsidered, *Journal of Common Market Studies*, 34, pp. 431-48.

[5] FARRELL, M.J. (1957) The Measurement of Productive Efficiency, *Journal of the Royal Statistical Society*, Series A, General, 120(3), pp. 253-82.

[6] FÄRE, R., GROSSKOPF, S., MORRIS M. and ZHANG Z. (1994a) Productivity growth, technical progress and efficiency in industrialized countries, *American Economic Review*, 79(5), pp. 1010-30.

[7] FÄRE, R., GROSSKOPF, S. and LOVELL, C. A, KNOX. (1994b) *Production Frontiers*. Cambridge University Press, Cambridge UK.

[8] GARDINER, B., MARTIN R. and TYLER, P. (2004) Competitiveness, productivity and economic growth across Europe, *Regional Studies*, 38, pp. 1045-1067.

[9] GIJBELS, I., MAMMEN, E., PARK, B. U. and SIMAR, L. (1999) On estimation of monotone and concave frontier functions, *Journal of the American Statistical Association*, 94, pp. 220-228.

[10] GROSSKOPF, S. (1993) Efficiency and productivity, in *The Measurement of Productive Efficiency: Techniques and Applications*, 160-194, Fried, H.O., Lovell, C.A.K. and Smith S.S. (Eds.), Oxford University Press

[11] HENDERSON, D, J. and RUSSELL, R.R. (2005): Human Capital and Convergence: A Production-Frontier Approach, *International Economic Review*, 46(4), pp. 1167-1205.

[12] HENDERSON, D, J. and ZELENYUK, V. (2006): Testing for (Efficiency) Catching-up. *Southern Economic Journal*, forthcoming.

[13] KNEIP, A., SIMAR, L. and WILSON, P. W. (1999) Asymptotics for DEA Estimators in Non-parametric Frontier Models, Discussion paper 0317, Institut de Statistique, UCL.

[14] KUMAR, S. and RUSSELL R. (2002) Technological Change, Technological Catch-up, and Capital Deepening: Relative contributions to Growth and Convergence, *The American Economic Review*, 92(3), pp. 527-548.

[15] KAMPS, C. (2005) The Dynamic Effects of Public Capital: VAR Evidence for 22 OECD Countries, *International Tax and Public Finance*, 12 (4), pp. 533-558.

[16] KAMPS, C. (2006) New Estimates of Government Net Capital Stocks for 22 OECD Countries 1960-2001". IMF Staff Papers 53(1).

[17] LOS, B. and TIMMER, M.P. (2005), The 'Appropriate Technology' Explanation of Productivity Growth Differentials: An Empirical Approach, *Journal of Development Economics*, 77(2), pp.517-531.

[18] MAUDOS, J., PASTOR, J.M. and SERRANO, L. (2000) Efficiency and productive specialization: An application to the Spanish Regions, *Regional Studies*, 34(9), pp. 829-842.

[19] MAUDOS, J., PASTOR, J.M. and SERRANO, L. (2000) Convergence in OECD countries: technical change, efficiency and productivity, *Applied Economics*, 32, pp. 757-765.

[20] NEVEN, D. and GOUYETTE, C. (1995) Regional Convergence in the European Community, *Journal of Common Market Studies*, 33, pp. 47-65.

[21] MAS, M., PEREZ, F., and URIEL, E. (2000) Estimation of the stock of capital in Spain, *Review of Income and Wealth*, 46(1), pp. 103-16.

[22] MARROCU, M., PACI P. and PALA R. (2000) Estimation of total factor productivity for regions and sectors in Italy. A panel cointegration approach, Contributi di Ricerca CRENoS, 00/16.

[23] O'MAHONEY, M. (1996) Measures of fixed capital stocks in the post-war period: a five country study, in N.F.R. Crafts and B. van Ark eds, *Quantitative aspects of Post-war European Growth*, Cambridge University Press.

[24] PACI, R. and PUSCEDDU, N. 2000 Stima dello stock di capitale nelle regioni italiane, Rassegna Economica, *Quaderni di Ricerca*, pp. 97-118.

[25] PRUD'HOMME, R. (1996) Assessing the role of infrastructure in France by means of regionally estimated production functions, in Batten, C.K. *Infrastructure and the Complexity of Economic Development*, Berlin Heidelberg, pp. 37-47.

[26] QUAH, D. (1996) Regional convergence clusters across Europe, *European Economic Review*, 40(3-5), pp. 951-958.

[27] SHEATER, S. J. and JONES, M. C. A Reliable Data-Based Bandwidth Selection Method for Kernel Density Estimation, *Journal of the Royal Statistical Society.* Series B (Methodological), Vol. 53, No. 3, pp. 683-690.

[28] SILVERMAN, B.W. (1986) *Density Estimation.* Chapman&Hall, London.

[29] SIMAR, L. and WILSON, P. W. (1998) Sensitivity analysis of efficiency scores: How to bootstrap in non-parametric frontier models, *Management Science*, 44, pp. 49-61.

[30] SIMAR, L. and WILSON, P. W. (2000) A general methodology for bootstrapping in non-parametric frontier models. *Journal of Applied Statistics*, Vol. 27, No. 6, pp. 779-802.

[31] SIMAR, L. and WILSON, P. W. (2004) Performance of the Bootstrap for DEA estimators and Iterating the Principle, in *Handbook of Data Envelopment Analysis*, ed. by W.W Cooper, L.M. Seiford and J. Zhu, New York: Kluwer Academic Publishers, Inc., chapter 10, pp. 265-298.

[32] SIMAR, L. and WILSON, P. W. (2006) Statistical Inference in Non-parametric Frontier Models: Recent Developments and Perspectives, In *The Measurement of Productive Efficiency.* 2nd edition, chapter 4, ed. by H. Fried, C. A. K. Lovell and S.S. Schmidt, Oxford: Oxford University Press.

[33] SOLOW, R.W. (1957) Technical Change and the Aggregate Production Function, *The Review of Economics and Statistics*, 39, pp. 312-20.

[34] STEPHAN, A. (2000) Regional infrastructure policy and its impact on productivity: A comparison of Germany and France, *Applied Economics Quarterly* 46, pp. 327-356.

[35] TONDL, G. (1999) The Changing Pattern of Regional Convergence in Europe, in: *Jahrbuch für Regionalwissenschaft*, 19:1, pp. 1-33.

TABLE 1	Eff.1980	Bias Corr.	d ranking		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	Extremandura	0.49	0.48	0

TABLE 2	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**

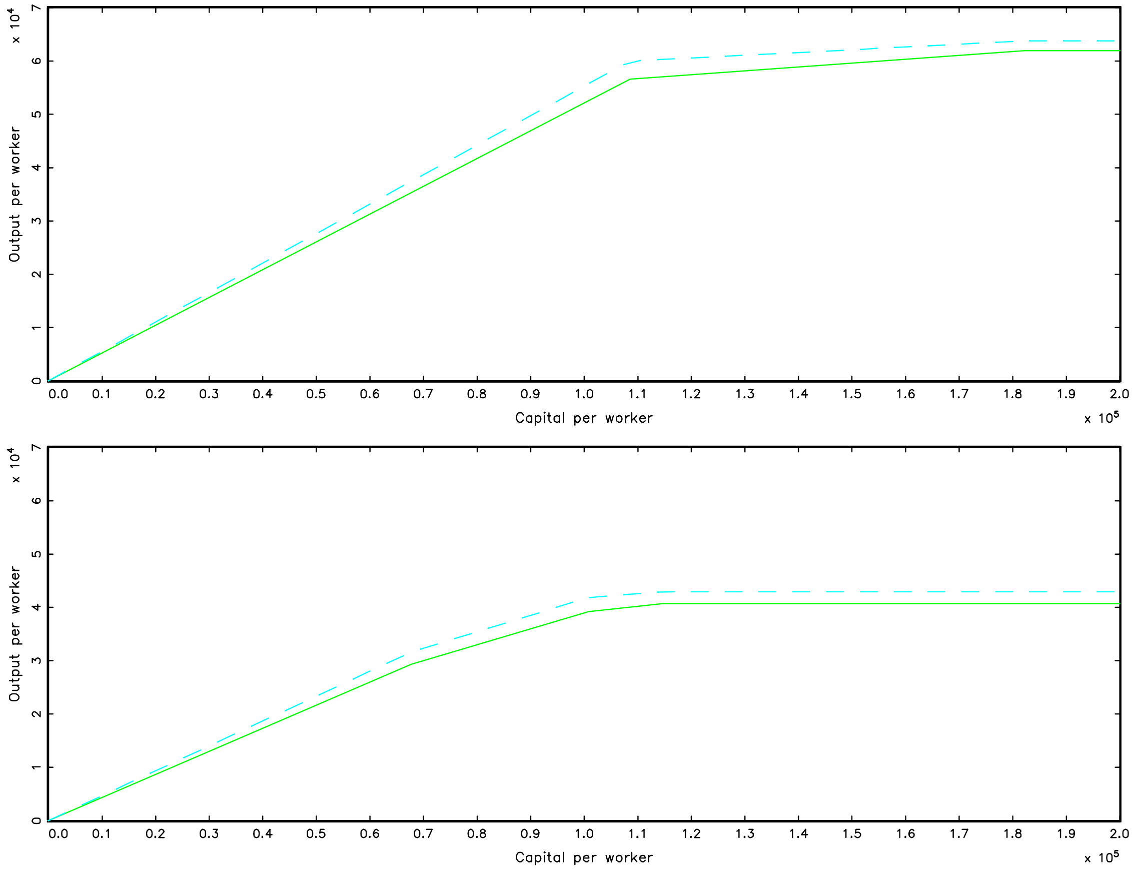

Figure 1: The constructed and bias-corrected technological frontiers in 1980 (below) and 2002 (above). Note, dotted lines refer to the bias-corrected frontiers.

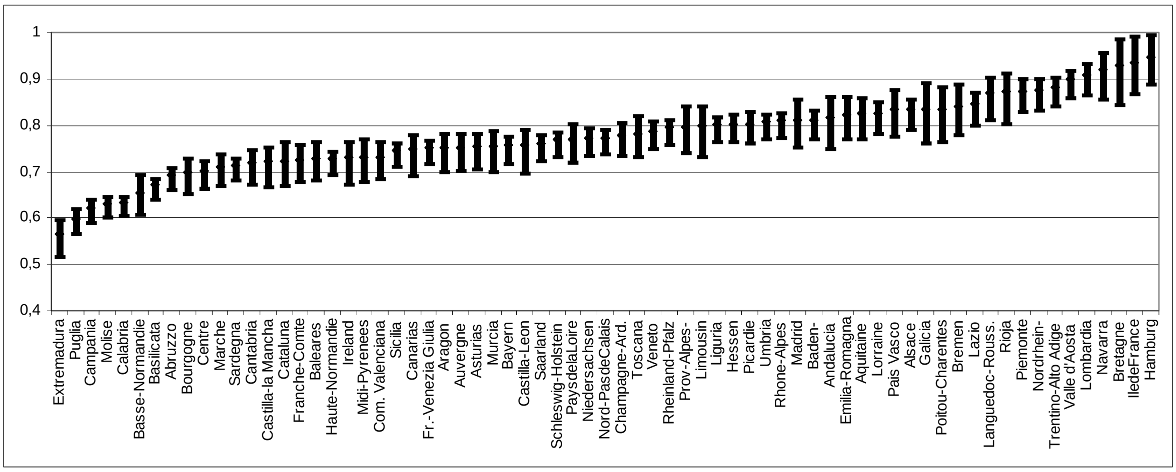

Figure 2: Efficiency levels and confidence intervals for all regions in 1980.

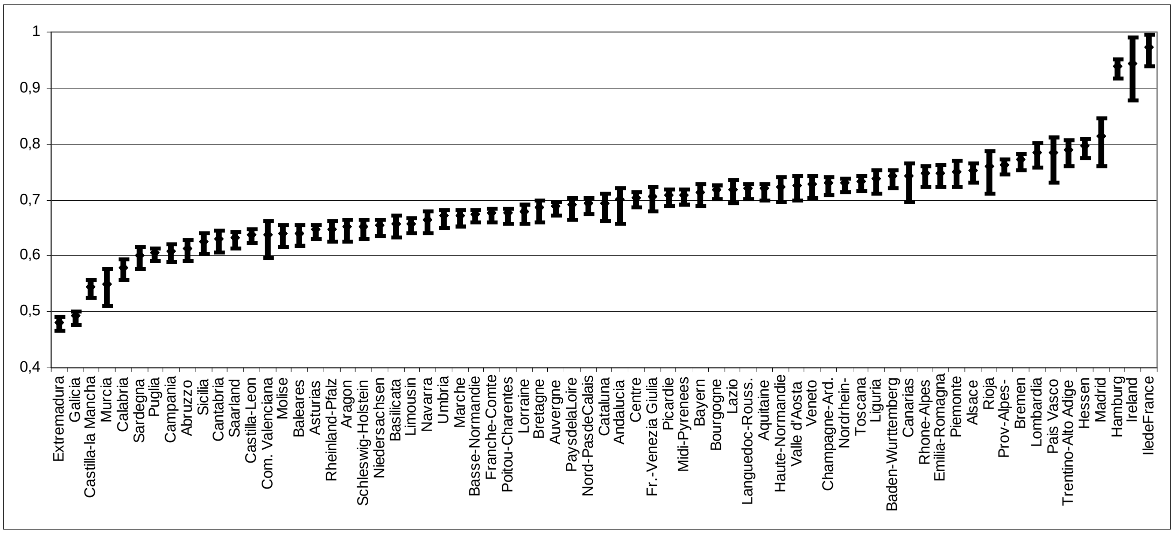

Figure 3: Efficiency levels and confidence intervals for all regions in 2002.

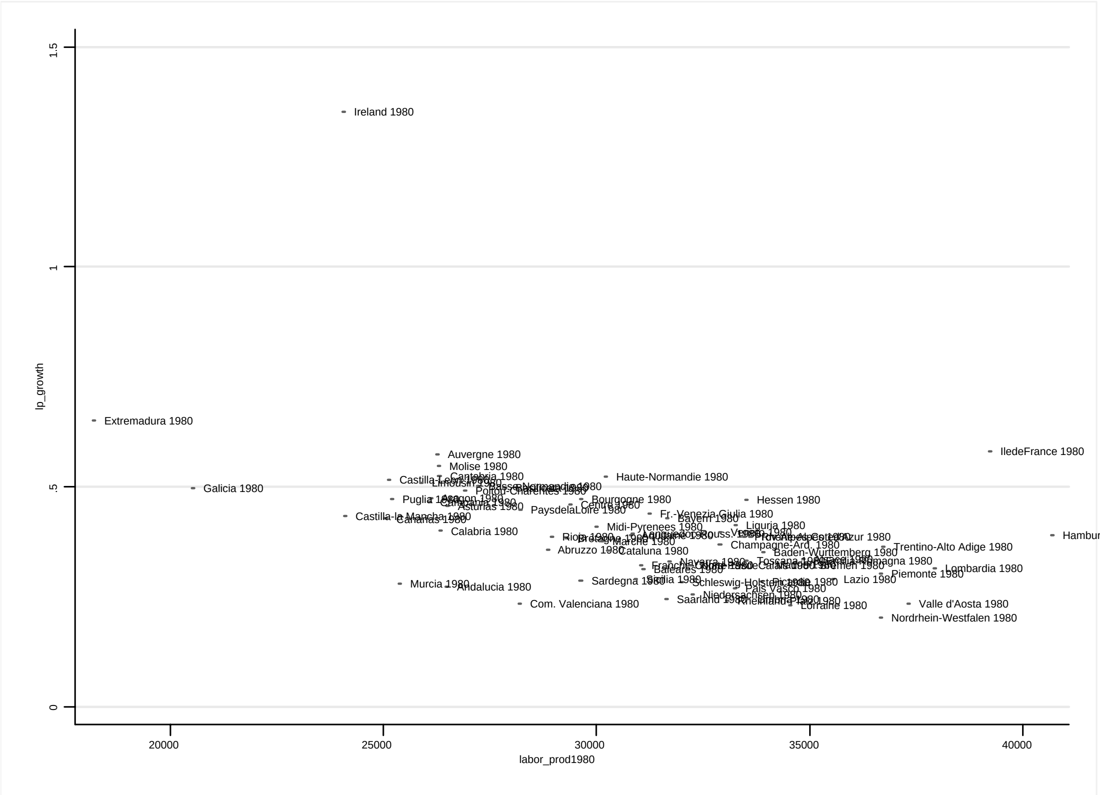

Figure 4: Labor productivity in 1980 (x-axis) versus labor producticity growth 1980-2002 (y-axis).

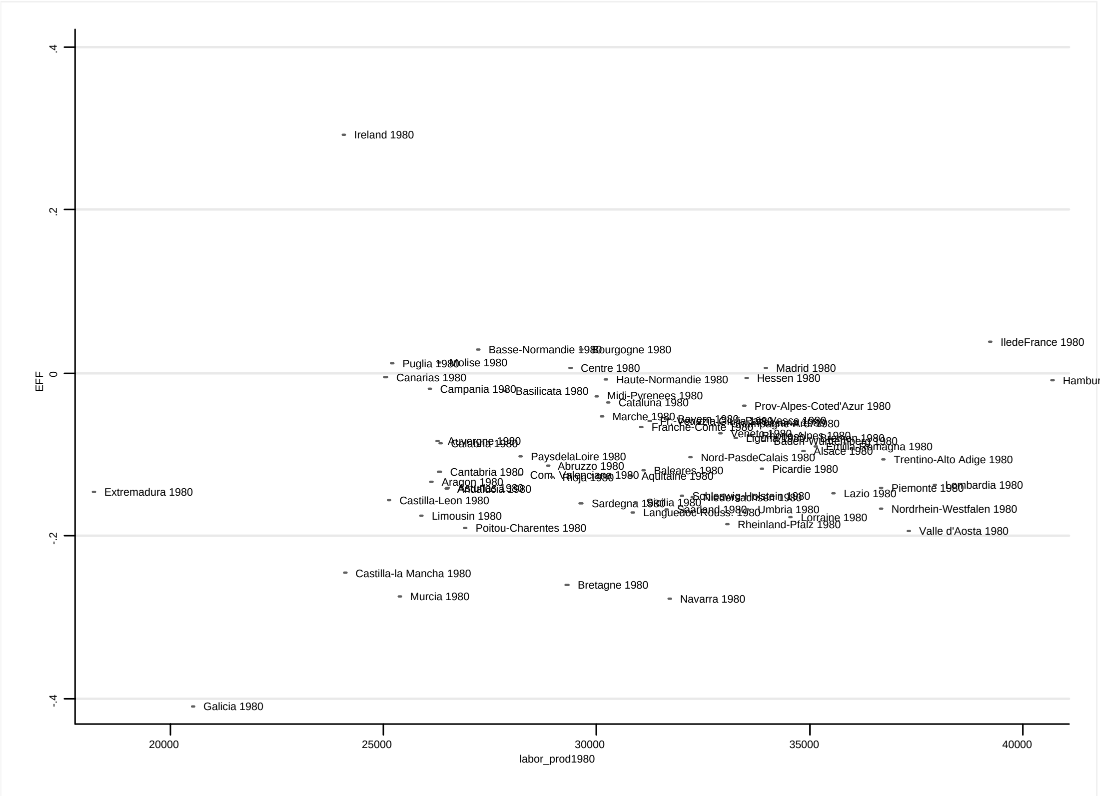

Figure 5: Labor productivity in 1980 (x-axis) versus relative change in efficiency 1980-2002 (y-axis).

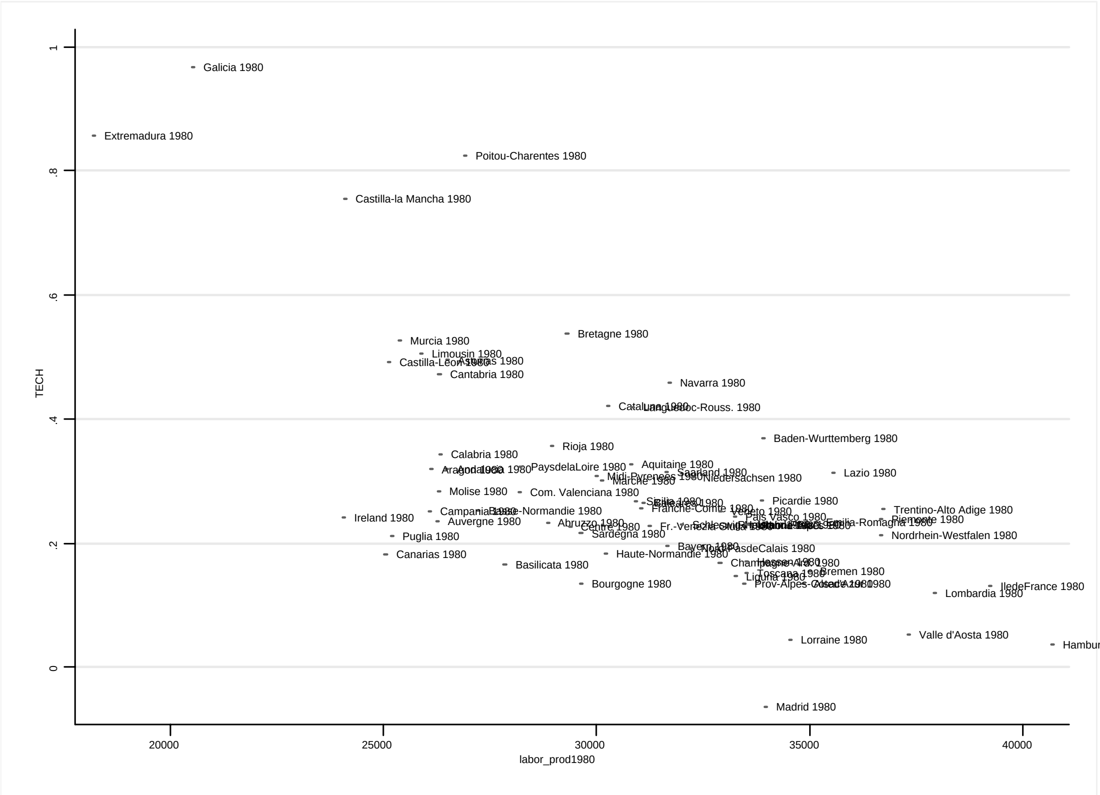

Figure 6: Labor productivity in 1980 (x-axis) versus relative change in technology 1980-2002 (y-axis).

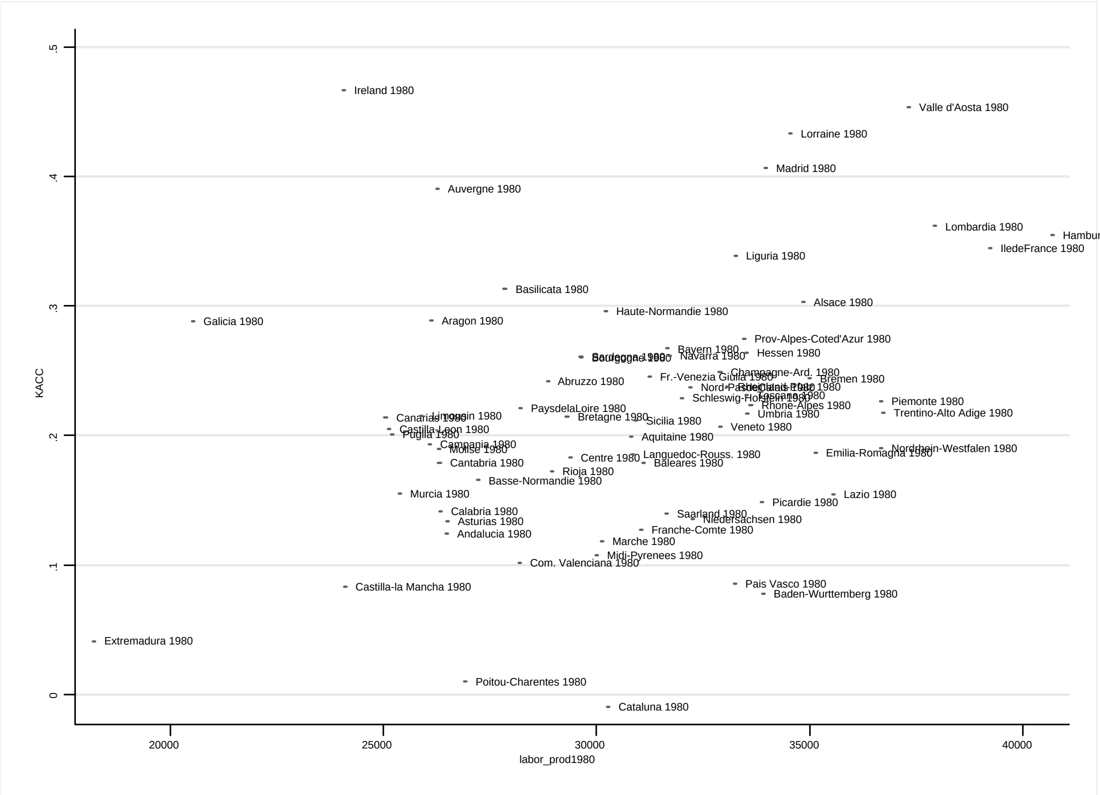

Figure 7: Labor productivity in 1980 (x-axis) versus relative capital accumulation 1980-2002 (y-axis).