Convergence or divergence?
An efficiency approach to European regional growth 1980-2002

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1 Introduction

Since the seminal articles written by Barro and Sala-i-Martin (1991, 1992, 1995), many studies have focused on the question of regional economic growth and convergence. The regional framework has often been proposed to test the neo-classical convergence hypothesis, since institutional factors are more similar across regions within a country than between nations. In the case of Western Europe this may even be true across nations, since institutions have become increasingly integrated after the formation of the European Union and the equalization of regional income differences is a pronounced goal within the union. However, recent studies have cast a doubt on the idea of regional convergence, instead reporting a slow-down in convergence after 1980 (Tondl: 1999; Fagerberg and Verspagen: 1996) or arguing that regions are converging into different regional clubs (Quah: 1996a).

As a result of these findings, the aim of this paper is twofold. First, it attempts to explore and describe the geographical patterns of growth and changes in the income distribution in 69 Western European NUTS 2-regions by employing a non-parametric technique[1]. Technological leaders, followers and regions that are falling behind will be identified to allow for a descriptive characterization of historical lead-lag patterns among the European regions. Second, the proximate driving forces behind the changes in labor productivity distributions will be investigated by decomposing changes in labor productivity into three factors: technological change, catch-up and capital deepening (Kumar and Russell: 2002).

In contrast to many earlier regional convergence studies that use standard regression or cluster analysis, Data Envelopment Analysis (DEA) will be used in order to allow for a non-parametric estimate of the production function. The DEA-approach introduces an important component into our thinking about economic growth: efficiency, the ability of a given region to fully exploit available resources. Therefore, the issue of convergence or divergence can be analyzed, not only in labor productivity levels, but also in terms of efficiency and catching-up.

[1] The dataset consists of 20 Italian, 20 French, 11 German, 17 Spanish NUTS 2-regions and Ireland. Due to present data constraint UK is excluded from the analysis.

2 Background

Theories on growth and convergence have tended to stress different factors as the driving forces of changes in income levels. In Solow (1956), capital accumulation is suggested as the main source of convergence between countries and regions. Based on the assumptions of decreasing marginal returns to capital, constant returns to scale and publicly available technology, regions with low capital endowments are predicted to grow faster than rich regions, where decreasing marginal returns to capital has started to set in. Hence, the model explains differences in regional productivity with differences in initial factor endowments. Given that all countries and regions produce under the same aggregated production function and that technology is universally available, all regions are predicted to converge to the same steady state ratios of capital and output per worker. However, the outcome is not unambiguous convergence to a common steady state in this model. If there are limits to technical diffusion or if regions differ in institutional properties that affect the substitutability between production factors, regions may converge to different steady states. Many scholars have therefore come to suggest that conditional convergence to different steady states can be found empirically, even though the unconditional convergence hypothesis has found little empirical support (Barro 1991, Barro and Sala-i-Martin 1991, Mankiw, Romer and Weil: 1992).

A competing perspective has been promoted by a diverse group of scholars, ranging from economic historians and evolutionary economists to researchers active in the fields of endogenous growth and new economic geography. Although differing among themselves, they share the view that innovations and technology diffusion is the main source of growth which opens up for possible divergence between countries and regions.

Much work in this tradition argues that the spatial diffusion of technology is far from instantaneous and that certain regions appear to be innovation leaders. The new economic geography school attributes regional differences to increasing returns to scale and positive externalities of production. By relaxing the neoclassical assumptions of perfect competition and constant returns to scale the new economic geography approach can explain why and how agglomeration economies occur without having to assume any initial regional differences in institutional setups or factor prices (for example Krugman: 1991, Fujita, Krugman and Venables: 1999). From this perspective, economic integration will increase the tendency for spatial agglomeration and specialization of economic activities by facilitating the flow of production factors to the agglomerative areas. Actually, many new economic geography models predict a "core-periphery"-pattern of productivity in equilibrium.

The perspective promoted by economic historians and evolutionary economists leave more room for understanding regional divergence as the outcome of path dependency in firm or regional leadership. Technological leadership emerges from the creation of knowledge that becomes embodied in the organizational routines of successful firms. When local knowledge spills over through inter-firm collaborations or professional networks, regional technological leaderships are created. Evolutionary economics treat agglomeration forces as an incentive and as a selection mechanism that can explain why economic activity becomes more and more spatially concentrated. But path dependency also plays an important role which implies that spatial processes can be explained without adding the forces of agglomeration (Boschma and Frenken: 2005).

The historical approach has on the other hand devoted much attention to the momentum of technology adoption and knowledge spillovers between regions as a converging force if the institutional setting is right. This hypothesis is famously know as the catch-up hypothesis and builds on the idea that lagging countries or regions may be able to catch up in economic growth by imitating technologies used by technological leaders (Abramowitz: 1986). However, the ability to do so is dependent of the "social capability" in the particular economy, and poorer countries will hence not automatically grow faster than rich ones, as the Solow-model predicts. Social capability is a highly localized phenomenon in this context and geography and history matters in order to explain convergence or divergence in these settings.

In summation, growth theories have built on differing assumptions about the mechanisms of economic development which has lead to conflicting hypothesis about the link between growth and regional inequality. The neoclassical growth model predicts convergence in labor productivity mainly driven by capital accumulation; whereas the alternative explanations hold that the patterns technological change is responsible for the economic outcome of different regions. The new geography school predicts divergence between regions and the emergence of core-periphery geographical structures. Economic historians generally focus on the possibility for technical diffusion and catching up of initially backward regions, a force that can drive convergence under certain institutional settings.

However, a question that has received surprisingly little attention in the empirical debate is if, and to what extent, regional convergence varies with the economic cycle (Gardiner, Martin and Tyler: 2004)[2]. Investigating the evolution of the regional labor productivity distribution in Western Europe in relation to the economic cycle and with a clear focus on the driving forces of changes in the labor productivity distributions may shed some light on these issues.

2.1 Earlier empirical studies

Methodologically, the vast majority of earlier empirical growth and convergence studies have evolved from standard cross-country regression analyses that take a negative correlation between initial income and average annual growth in subsequent periods as evidence of the β-convergence hypothesis. However, the appropriateness of this method has been criticised by Quah (1993), who showed that an inverse relationship between income and growth is consistent with a stable cross-country variance. Instead, Quah suggests that the issue of convergence should be related to the evolution of the whole income distribution. Employing a distribution dynamics approach, Quah describes the

[2] Gardiner, Martin and Tyler (2004: 1056) specify that EU experienced two major business cycles between 1980 and 2001: recession in early 1980s and 1990s and recovery and boom in the second halves of the two decades. Following the structural analysis school (Schön: 2000) the whole period after 1973 can be seen as one economic cycle that builds on a new techno economic paradigm. The issue whether regional convergence varies with the progress of two structural cycles will be investigated in future articles that make use of regional time series from 1950.

evolution of the cross country per capita income distribution between 1960 and 1988 as increasingly polarized into "twin peaks" of rich and poor countries. Epstein, Howlett and Schulze (2003) extend the approach to cover income distributions from 1870 to 1992, suggesting that convergence was a temporary phenomenon mainly found in the period after the World War II, but that it gave way to polarization in the post-golden age period.

The distribution dynamics approach suggested by Quah has also become popular in order to investigate whether convergence has taken place between the regions of EU. Pioneering these regional convergence studies, Quah (1996a) found that the income distribution of 78 NUTS 2-regions in Western Europe displayed a similar pattern of increased bipolarization between 1980 and 1989. Cheshire and Magrini (2000: 470) found high persistency in the income distribution of 122 Functional Urban Regions (FURs, a geographical unit different from Eurostat's NUTS classification) as well as a long-run tendency for a group of high income city-regions consisting of Hamburg, Stuttgart, Munich, Frankfurt and Düsseldorf and Paris to grow away from the rest of the income distribution between 1978 and 1994.

An important distinction between the majority of earlier growth and convergence studies and the present study is that the former have focused on regional convergence in income, i.e. GDP per capita levels whereas this study deals with labor productivity (GDP per worker). It shall be pointed out that the neoclassical theoretical growth models actually only make predictions about labor productivity (GDP per worker) and not income, as key differences between endogenous growth theories and the neoclassical Solow-model are the assumptions about the nature of the aggregated production function. Both models rely however on the assumption of full employment, although it has been shown that unemployment and labor force participation rates play and important role in predicting regional incomes (Boldrin and Canova: 2001, Gardiner, Martin and Tyler: 2004).

3 Data

The DEA-analysis requires data on regional inputs (capital and labor) and outputs (measured as gross value added at market prices). Data on regional output (GVA) and labor is taken from Cambridge Econometrics Data set.[3] The regional disaggregation follows Eurostat's NUTS classification system and all data are measured in 1995 Euros.[4] Figure 1 shows a kernel density diagram[5] of the distribution of output (gross value added, GVA) per worker in the 69 Western European regions that are included in the analysis between 1980 and 2002. In 1980 the distribution displayed a clear single peak just below its average productivity level. In 2002 the variance of the distribution has become larger

[3] The data set builds on Regio Eurostat database, OECD Territorial Data base, National databases and data from private bodies, e.g. trade organizations.

[4] All data is deflated on the country sectoral level and conversions into Euro follow the 1995 official exchange rate. Following Boldrin and Canova (2001) PPP-adjusted exchange rates are not used, since their interpretation in productivity studies are not straightforward, see appendix B for a further discussion of PPS versus actual exchange rates.

[5] The Kernel density function is a non-parametric estimate of the density of the sample. It can basically be thought of as a smoothed histogram. All Kernels are based on Epanechnikov's weighting and the bandwidths are calculated according to Silverman's (1982) recommendation.

with two clear high peaks, and an emerging third peak at very high output per worker levels. This suggests that the amount of regions in the middle-productivity group has

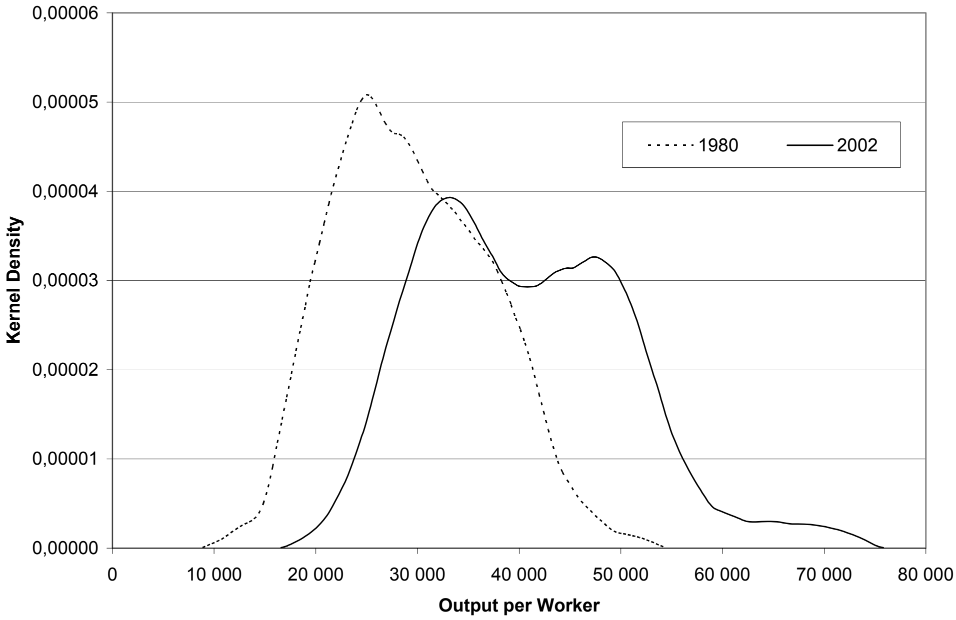

Figure 1. Kernel distribution of output per worker in 69 European regions in 1980 and 2002.

diminished and that the regional map of Western Europe has become increasingly divided.[6]

Coherent regional data on capital stocks is currently unavailable and therefore capital stocks have to be estimated using the perpetual inventory method (PIM) from regional investment series. Yearly regional investment series were obtained from Cambridge Econometrics. In order to estimate regional capital stocks, I have built extensively on earlier research when calculating and benchmarking the relative share of a region's capital stock to the national stock (Paci and Pusceddu: 2000, Marrocu and Paci: 2000, Stephan: 2000, Mas, Perez and Uriel: 2000, Prud'homme: 1996).

However, differing underlying assumptions of average service lives often induce incomparability between national capital stocks (O'Mahony: 1996: 178). In order to avoid any systematic biases in the level of the regional stocks due to differing national assumptions, a standardized set of capital stocks have been used as national benchmarks (Kamps: 2001). Further description of the capital stocks can be found in appendix B.

4 Method

The study utilizes Data Envelopment Analysis (DEA) to non-parametrically estimate production functions that serve as basis for the decomposition of labor productivity growth into three causal factors. The DEA approach to growth accounting was pioneered by Färe et al (1994) who decomposed the labor productivity increases in 17 OECD countries 1977-1988 into technical change and efficiency change. The approach was recently extended to incorporate capital accumulation as a source of labor productivity

[6] The labor productivity distributions do not change if UK regions at NUTS 2 are added

growth by Kumar and Russell (2002), who also related sources of labor productivity growth to the emerging bipolarization of world income documented by Quah using national data from Penn World Tables. Other studies in this tradition that use national data to cover the period from 1960 and onwards are Los and Timmer (2005) and Badunenko and Zelenyuk (2004).

DEA is a data-driven non-parametric linear programming method that neither requires any a priori specifications of the functional form, nor any assumption about market structure and absence of market imperfections, as it allows different regions to produce output at different levels of efficiency. This stands in contrast to traditional econometric and growth accounting studies that rely on specific functional forms of the production technology. However, the approach is more sensitive to noise and outliers in the data and it used to be difficult to present some measure of uncertainty (e.g. confidence intervals) to the DEA-scores.[7] To combat these problems, bootstrapping methods that can give standard errors and confidence intervals to the DEA-estimates have been introduced lately (see for example Henderson and Zelenyuk (2004) for bootstrapping of DEA-scores).

4.1 Production frontiers

In this study we let each region use capital and labor in order to produce output (GVA). The basic idea is thereafter to construct a technological frontier consisting of the regions that have used their combinations of inputs most efficiently. More formally, under the assumption of constant returns to scale, the frontier is the upper boundary of the smallest convex cone that fits all regional observations.

In most DEA studies the production frontier is calculated using data from the current period only, but this study will include the history of data up to current date. The advantage of calculating the production function in this inter-temporal way is first of all that "technical regress" is ruled out, since the sequential construction of the frontier does not let it shift inward. Technical regress would involve forgetting advancements that were made in the past and is hard to defend from a knowledge perspective. Secondly, the inter-temporal construction rules out the possibility that short-term fluctuations in output affect the production possibility frontiers. Thirdly, the construction follows Abramowitz definition of catching-up, as latecomers are able to catch-up with the historical technological leaders by imitating their technology.

In figure 2, two technological frontiers are constructed from the 69 regions; the lower frontier represents attainable output levels in 1980 whereas the higher one represents 2002. In this case the 2002 frontier consists solely of observations from 2002, but all historical data up to 2002 are included in estimating the frontier, so theoretically the frontier can consist of any best practice observation up to 2002. In appendix A, figure A2 displays the two samples of 69 regions in 1980 and 2002 evaluated against their corresponding production frontiers. As we can see, the vast majority of the included

[7] Another line of research dealing with efficiency has developed in the "Stochastic Frontier Regressions", especially the composed error approach. These methods are stochastic instead of deterministic and do produce standard errors and can be subject to hypothesis testing. However their drawback lies in the requirement of a functional form of the production technology, for example a Cobb-Douglas function.

regions are redundant in the construction of the frontier. The reason is that another region, or a linear combination of two other regions, can produce more output with the same use of inputs.

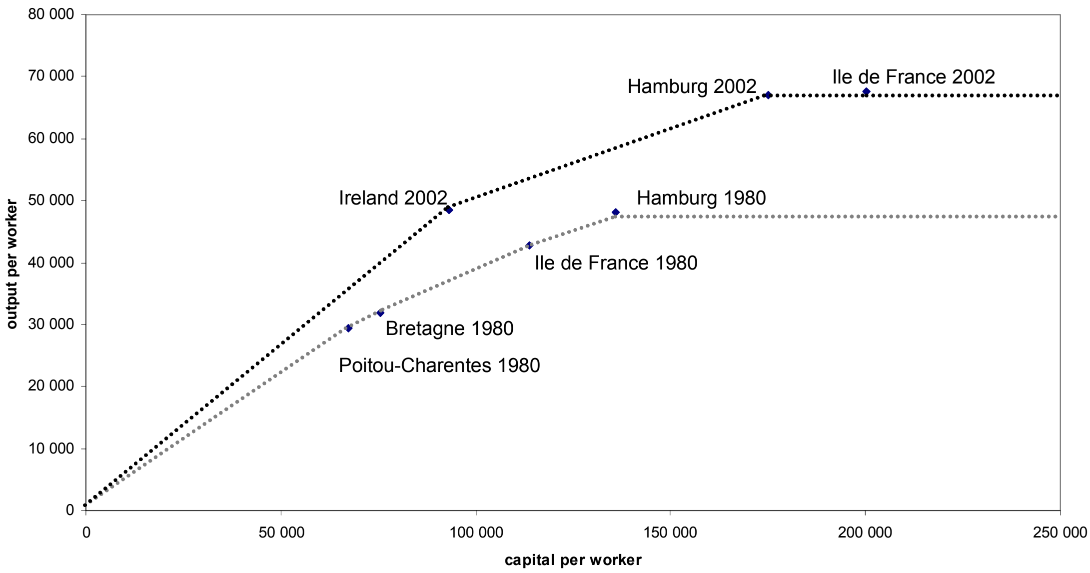

Figure 2. The technological frontiers in 1980 and 2002

4.2 Interpretations of efficiency and technology

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 only 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. The efficiency indices for the 69 regions calculated under the assumption of constant returns to scale are presented in table 1 in the appendix.[8]

Conceptually, the efficiency component is nothing but a residual that proxies for the aggregated effects of various factors other than capital and labor. Therefore, the production frontier and the associated indices should not be interpreted too literally. Malfunctioning institutions, poor organization or low human capital[9] may also cause

[8] In order to check the sensitivity of the result to the scale assumption, the efficiency indices were calculated under different scale assumptions (non-increasing, non-decreasing and varying returns to scale). Although a few individual regions were added to the technical frontier at extremely low and extremely high capital per worker ratios depending on the scale assumptions, the overall shape of the frontier that most regions were evaluated against remained surprisingly stable. Figure A1 in appendix A shows that the Kernel distribution of efficiency scores for 2002 is rather robust to changes in scale assumptions

[9] So far we will exclude human capital as a source of changes in labor productivity. However, many empirical and theoretical studies have suggested that human capital accumulation accounts for a large proportion of productivity growth, so depending on data availability a regional measure

"technological inefficiency" in a certain region. It is also important to keep in mind that the frontier is only defined relative to the best practice regions in the sample. Thus, there is always the possibility that the "true" technological frontier lies above the constructed frontier. Productivity shortfall and catch-up will be measured compared to the most efficient region is this particular sample.

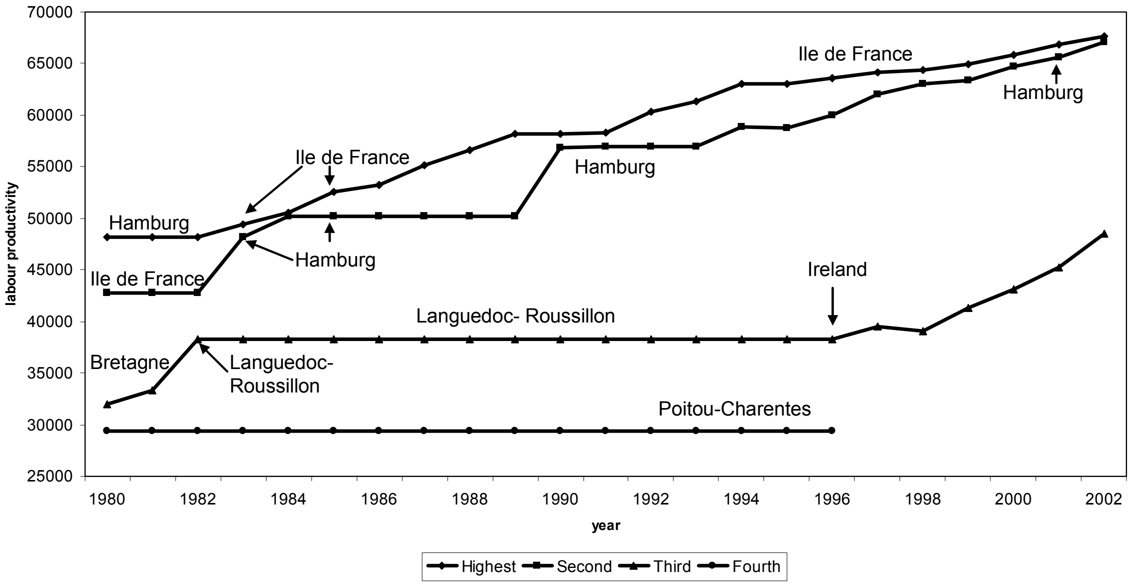

Figure 3. Evolution of the technological frontier at different capital per worker levels 1980-2002.

5 Leaders and followers

An interesting feature of the empirically constructed productivity frontiers in figure 2 is that they are not supporting the notion of Hicks-neutral technological change. If technology were in fact Hicks-neutral it would mean that technological change would be independent on the capital per worker ratio and that the frontier of 2002 would be shifted vertically by the same proportion compared to the front of 1980. Instead, shifts in the technological frontier have occurred mostly among the highly capitalized regions. Between 1980 and 2002 the frontier was shifted roughly by 40 % at Ile de France's capital per worker level. At Ireland's capital per worker level the frontier was however only shifted by about 26 % and by even less at lower capital ratios.

In addition, the shift that occurred at medium levels of capital per worker was solely due to the impressing labor productivity increase of Ireland. If it was not for the Irish experience, the frontier would not have shifted outward at all at low capital per worker levels during the investigated time period. This finding suggests that there are barriers to technological adoption at low capital per worker levels, since poorly

of the stock of human capital can hopefully be included in the future. See Henderson and Russell (2004) for a decomposition of labor productivity into human capital accumulation based on DEA.

capitalized regions in this sub sample do not seem to benefit to the same amount from advancements of the technological frontier.

Comparing the plots of regions evaluated against the constructed frontiers in figure A2 to the predictions of the Solow-model reveals a quite unexpected pattern. If the Solow model were taken literally, we would find all regions located on the frontier, since the Solow model assumes that all regions use the same technology and leaves no room for inefficiency and market imperfections. In addition, the Solow model predicts that regions would be moving along the production frontiers in accumulating capital and that their capital and output ratios would gradually converge. Instead, the plot in figure A2 suggests that regions are not converging at all but that the spread of capital and output per worker has rather increased somewhat between 1980 and 2002. The plot also illustrates the emerging bipolarization since many "middle-productivity" regions in 1980 have fallen behind the frontier relatively in 2002.

In figure 3 a time series of the "best practice" regions at different capital per worker levels is displayed. It is apparent that the technological has frontier has successively been pushed outward by the capital intensive regions Ile de France and Hamburg during the investigated time period, whereas very little technical chance has occurred at low capital per worker levels. The successive productivity increase of Hamburg and Ile de France follow the business cycle pattern laid out by Gardiner, Martin and Tyler (2004) to some extent since we can identify a stronger productivity increase during the second half of the 1980s. However, the upswing in the late 1990s was accompanied by comparatively weaker increases in the best practice labor productivity levels.

As opposed to the successive productivity increases of Hamburg and Ile de France, the technical frontier at low capital per worker levels did not shift at all until 1997 when Ireland started to push it outwards. It can be argued that Ireland managed to take advantage of the general upswing in the late 1990s when making the transition into becoming a technological leader at lower capital per worker ratios. The slower productivity increases of the leaders Ile de France and Hamburg and the strong boost of Ireland could suggest that some "catching-up" took place during the upswing in the late 1990s. But the Irish expedience is exceptional and not part of a general pattern. Instead, the most striking general feature during this time period is one of "falling behind". The efficiency scores in table 1 in the appendix confirms this picture, as only 11 regions out of 69 were actually able to increase their efficiency and catch-up with the technical frontier between 1980 and 2002.

6 The Decomposition Framework

In order to analyze factors affecting productivity growth in a certain region, a decomposition suggested by Kumar and Russell (2002: 534-535) is used. The decomposition is based on the calculated efficiency indices for each region in the two reference periods and exploits the assumption of constant returns to scale. Denoting output per worker as y_b in the base period and y_c in the current period, a region's relative change in labor productivity between the two periods can be decomposed into the following three terms:

$$y_c / y_b = (1+\Delta EFF) \times (1+\Delta TECH) \times (1+\Delta KACC) \tag{1}$$

The first right-hand term will then measure 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 will measure the effects of shifts in the frontier itself (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).

Unfortunately, the separation of capital accumulation and technical change is not path-independent since technology change is not Hicks neutral, but rather depending on the capital to labor ratio. This means that it matters whether the shift in the frontier is measured at the base or at the current period's capital per worker ratio. In order to avoid this arbitrariness the decomposition has been carried out using both normalizations. When measuring technical change at the base period, capital accumulation is given relatively more importance than when the decomposition is carried out at the current period's capital ratios. In table 2 in the appendix, the decomposed indices are presented as the geometric averages of the two normalizations.

However, the basic result is that capital accumulation and technological change have played roughly equally large roles for the labor productivity growth in the 69 regions during 1980 to 2002 and is not very sensitive to which normalization we chose for technical change. From table 2 we find that the average relative contribution of technical change is 0.24 using the geometric average. If technical change is normalized on the 1980 capital per worker ratios, the average relative contribution of technology becomes slightly smaller at 0.21 since the technical shift is smaller at low capital per worker levels. Normalizing on 2002's capital ratio gives that the relative contribution of technology is 0.27.

Moreover, it shall be emphasized that the problem of path dependency is endemic to the task of measuring technical change, and that most commonly is 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.

6.1 Distribution dynamics

In order to use the decomposed indices to analyze the driving forces behind the emerging bipolarization of the labor productivity distribution between 1980 and 2002, we will now turn to the distribution dynamics approach suggested by Quah (1993, 1997). This method will introduce a causal element into the observed changes of the distribution by utilizing the three decomposed elements behind labor productivity growth to assess which one of them that plays the largest role in the emergence of a bimodal distribution.

Following Kumar and Russell (2002, p. 541-544) we can rewrite the labor productivity changes in equation 1 as follows

$$y_c = \left[(1+\Delta EFF)\times(1+\Delta TECH)\times(1+\Delta KACC)\right]y_b \tag{2}$$

where b indicates the base period (1980) and c indicates the current period (2002). This small rearrangement describes the current labor productivity distribution as the product of the three sources of labor productivity growth multiplied with the initial labor productivity distribution. Rewriting the changes in labor productivity in this fashion allows us to separate the effects of a single factor for the change in the income distribution by creating a counterfactual income distribution, where we single out one of the three factors.

For example, in order to isolate the effects on the labor productivity distribution that comes from relative efficiency changes we can create the following counterfactual variable

$$y_c^{Cont} = (1+\Delta EFF)\times y_b \tag{3}$$

The distribution of this variable is shown in figure 4 together with the two actual labor productivity distributions between 1980 and 2002. The counterfactual variable displays how the labor productivity distribution would look like in 2002 if all labor productivity changes were driven only by regions improving their efficiency and producing output closer to the technological frontier. That is, if all of the actual observed increase in labor productivity were due to efficiency changes the counterfactual 2002 distribution would be identical to the real. That would at the same time mean that capital accumulation and technological change had played no role at all in explaining labor productivity growth, because singling out efficiency means that the other two factors are kept constant at their 1980 values.

From the counterfactual graph in figure 4 it is evident that efficiency improvements have played a negative role during the investigated time period. That is, without any capital accumulation and a stationary technological frontier, the mean of the counterfactual distribution in 2002 would actually have even been *lower* than it in 1980. This confirms our earlier finding that a majority of regions are falling behind the productivity frontier during the investigated time period. The shape of the counterfactual distribution is very similar to the initial labor productivity distribution, showing that both high and low labor productivity regions in 1980 are falling behind their respective frontiers. The conclusion similarly implies that a combination of the other two factors, capital accumulation and technological change, are responsible for all of the observed changes in labor productivity between 1980 and 2002.

Figure 4. The counterfactual labor productivity distribution in 2002, isolating the effect of efficiency change between 1980 and 2002 (assuming no technical change and no capital accumulation). Plotted against actual labor productivity change 1980-2002

Figure 5. The counterfactual distribution in 2002, isolating the effect of capital accumulation (assuming no efficiency improvements and no technical change). Plotted against actual labor productivity change 1980-2002

Figure 6. Counterfactual labor productivity distribution in 2002, isolating the effect of technical change between 1980 and 2002 (assuming no efficiency change and no capital accumulation). Plotted against actual labor productivity change 1980-2002

Figure 7. The counterfactual labor productivity distributions in 2002, isolating the effects of efficiency change, capital accumulation and technical change between 1980 and 2002.

The effect of capital accumulation is singled out in a parallel manner as the efficiency changes in equation 2 and the resulting counterfactual distribution is shown in figure 5. From the picture we find that capital accumulation as a single factor raises the mean of the counterfactual distribution to nearly coincide with the actual mean in 2002. Thus, capital accumulation has been a strong contributor to labor productivity increases in the sample. However, capital accumulation did not seem to have had the converging effects on labor productivity the Solow-model predicts. Instead, the counterfactual distribution displays a larger variance than the actual distribution in 2002. Rather than a pattern in which regions with low initial capital are accumulating relatively more capital per worker, the observed patterns is that all regions have accumulated capital, but that the high productivity regions have accumulated somewhat more. This pattern calls for additional analysis, but can perhaps be explained by agglomerative or path-dependent forces in high productivity regions. Figure 5 also shows that capital accumulation cannot explain the increased bipolarization of the distribution, only some of its increased variance.

In figure 6, the separate effects of technical change are presented. It seems that movements of the technological frontier are also driving the increased mean of the distribution, albeit a little less than capital accumulation. Interestingly enough it seems that the variance of the counterfactual distribution is slightly lower that of the actual distribution in 2002. This would suggest that both low productivity and high productivity regions have benefited from the *absolute* shifts in the technical frontier when they have occurred, although virtually no regions have improved their *relative* positions. However, due to the non-neutral nature of technological change regions that were operating on higher productivity levels have benefited slightly more, resulting in a tendency for polarization in the counterfactual labor productivity distribution.

In figure 7 the three counterfactual distributions are displayed together. It is clear from the picture that capital accumulation and technical change have had differing impacts on the shape of the labor productivity distribution between 1980 and 2002. A question for future research is if this pattern has been stable during the whole time period or if it is possible to distinguish changing impacts of the three decomposed factors during different sub-periods.

In summary the distribution dynamics analysis shows that the economic hierarchy of the 69 regions remained surprisingly stable over the investigated years. Hardly any regions have improved their relative efficiency and caught-up with the technological leaders. Instead, capital accumulation and technological change appear to explain all of the observed increases in labor productivity. Although the two forces have been roughly of equal importance in increasing the mean of the labor productivity distribution, capital accumulation has had a tendency to increase its variance, whereas the pattern of technological change appears to have introduced its observed bimodality in 2002.

7 Conclusion

Economic historians and many neoclassical economists have often seen increased globalization and harmonization of international institutions as a major force behind catch-up and convergence. But although the integration of Western European markets accelerated during the investigated time period this study shows that regional convergence and catch-up have been virtually absent after 1980. Instead, the period is characterized by bipolarization of the labor productivity distribution and a majority of regions "falling behind". The empirical construction of the technological frontiers discerns Hamburg and Ile de France as productivity leaders and shows that their lead has remained unthreatened since 1980. This finding confirms that there exists a subgroup of high R&D, high income regions in Europe with an internal dynamics of their own, as found by earlier studies (Cheshire and Magrini: 2000).

The tendency of capital accumulation to have a diverging effect on the labor productivity distribution seem to suggest that capital received its highest returns in regions with initially high productivity. In combination with the non-neutral nature of the technological shifts capital accumulation and technological change seems to have been mutually reinforcing each other. The argument that the integration of Western European regions has contributed to the concentration of economic activities in core European areas does therefore receive some support from the analysis.

However, the productivity performance of Ireland does not at all convey to this core-periphery pattern. Despite its peripheral location, Ireland has managed to attract leading high-technology companies through a rather aggressive policy of "industrialization by invitation". Today, Ireland is the fifth-largest producer and second-largest exporter of packaged software in the world - second only to the United States. Some observers argue that this miracle started already in the 1960s when the government invested heavily in higher education and in the formation of technical skills in electronics and computer-related disciplines through a system of regional technical colleges (Fortin: 2001: 23). With Abramowitz words it could be argued that Ireland started as "technologically backward but socially advanced" when producing at only 74 % of potential output in 1980.

Therefore the overall conclusion of this study is that the pattern of technological diffusion appears to be responsible for the emerging bimodality of the labor productivity distribution in the post-golden age period. As technology have augmented capital and labor the most at high capital per worker levels, the low and middle productivity regions have fallen increasingly short of the frontier. Even though capital accumulation has helped to increase output in low-productivity regions, the absence of efficiency improvements or catching-up means that regions needed to produce according to very capital intensive technologies in order to fully enjoy the technological advancements being made at the frontier. The only region that is an exception to this pattern and caught-up without initially high capital-per-worker levels has followed an explicit policy of technology adoption by attracting high skilled companies through tax subsidies. This seem to imply that technological diffusion in the post-golden age was far from a mechanical process spurred by increased openness to trade, harmonization of international institutions and decreasing marginal returns to capital.

8 Implications for future studies

The study raises a number of additional questions, especially concerning the relative importance of structural changes for the emerging pattern of regional bipolarization and falling behind. The analysis has shown that capital accumulation is an important source for labor productivity growth, but will regions that accumulate capital also achieve an industrial structure more alike to the technological leaders? And will a higher capital intensity in turn lead to that, in line with the argument that it takes time before a new structure can be operated efficiently, these regions eventually will increase their efficiency and catch-up? In addition, recent empirical findings have suggested that the regional bipolarization of labor productivity has been more related to the service sector than to manufacturing industries (Fotopoulos 2005). This finding can be contrasted with the rather unintuitive result that regional productivity convergence in traded activities has been slower than in non-traded activities (Gardiner, Martin and Tyler: 2004). It seems that the dynamics of the service sector, traded or non-traded, is far too important to leave aside in future analysis. An implication for future studies would therefore be to carry out the DEA analysis at different sectoral levels. Unfortunately, data on sectoral capital stocks at the regional level only exists for Italy and Spain at current date. The data needs therefore be estimated using regional sectoral investment series with the use of some assumption about the initial industrial structure of the capital stocks.

Appendix A

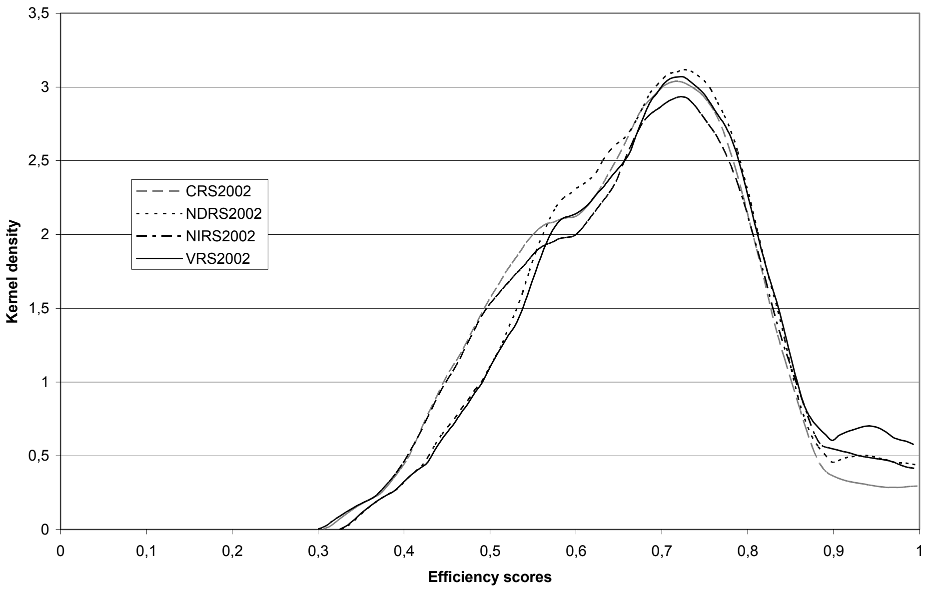

Figure A1. Kernel distribution of efficiency scores in 2002, calculated under different assumptions about returns to scale. Constant Returns to Scale (CRS), Non Decreasing Returns to Scale (NDRS), Non Increasing Returns to Scale (NIRS) and Variable Returns to Scale (VRS).

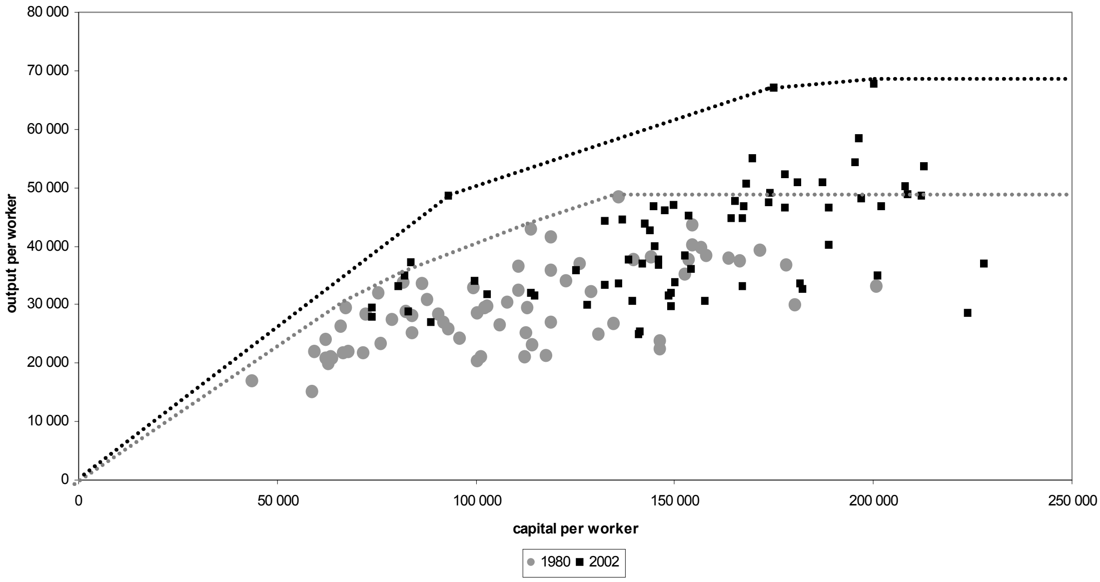

Figure A2. The distribution of regions plotted against the estimated frontiers in 1980 and 2002 respectively.

Table 1. **Efficiency scores for 69 regions, Constant Returns to Scale**

Region	**1980**	**2002**		**1980**	**2002**
Abruzzo	0.54	0.51	Languedoc-Rouss.	0.99	0.76
Alsace	0.79	0.76	Lazio	0.73	0.61
Andalucia	0.84	0.72	Liguria	0.56	0.62
Aquitaine	0.96	0.78	Limousin	0.91	0.71
Aragon	0.74	0.63	Lombardia	0.74	0.66
Asturias	0.74	0.60	Lorraine	0.78	0.69
Auvergne	0.84	0.72	Madrid	0.82	0.85
Baden-Wurttemberg	0.83	0.80	Marche	0.64	0.58
Baleares	0.69	0.55	Midi-Pyrenees	0.85	0.76
Basilicata	0.46	0.50	Molise	0.50	0.49
Basse-Normandie	0.75	0.69	Murcia	0.75	0.58
Bayern	0.78	0.79	Navarra	0.91	0.52
Bourgogne	0.77	0.73	Niedersachsen	0.79	0.71
Bremen	0.94	0.83	Nord-Pas de Calais	0.73	0.69
Bretagne	**1.00**	0.77	Nordrhein-Westfalen	0.90	0.78
Calabria	0.48	0.48	Pais Vasco	0.83	0.81
Campania	0.53	0.52	Pays de la Loire	0.87	0.76
Canarias	0.75	0.77	Picardie	0.81	0.71
Cantabria	0.71	0.51	Piemonte	0.74	0.62
Castilla-la Mancha	0.72	0.42	Poitou-Charentes	**1.00**	0.73
Castilla-Leon	0.76	0.59	Prov-Alpes-Coted'Azur	0.87	0.77
Cataluna	0.73	0.68	Puglia	0.52	0.53
Centre	0.69	0.72	Rheinland-Pfalz	0.81	0.72
Champagne-Ard.	0.81	0.73	Rhone-Alpes	0.76	0.76
Com. Valenciana	0.72	0.66	Rioja	0.88	0.79
Emilia-Romagna	0.78	0.64	Saarland	0.78	0.69
Extremadura	0.59	0.42	Sardegna	0.49	0.48
Fr.-Venezia Giulia	0.59	0.58	Schleswig-Holstein	0.79	0.72
Franche-Comte	0.75	0.69	Sicilia	0.53	0.52
Galicia	0.89	0.43	Toscana	0.73	0.64
Hamburg	**1.00**	**1.00**	Trentino-Alto Adige	0.69	0.60
Haute-Normandie	0.68	0.74	Umbria	0.61	0.58
Hessen	0.82	0.86	Valle d'Aosta	0.62	0.55
Ile de France	**1.00**	**1.00**	Veneto	0.65	0.62
Ireland	0.74	**1.00**			

Source: The efficiency calculations were carried out by the author, using the software EMS, available at http://www.wiso.uni-dortmund.de/lsfg/or/scheel/ems/

Table 2. **Percentage change of tripartite decomposition indices 1980 to 2002**

	Δ Y/L	EFF	KACC	TECH		Δ Y/L	EFF	KACC	TECH
Abruzzo	0.36	-0.05	0.25	0.13	Languedoc-Rouss.	0.39	-0.23	0.27	0.43
Alsace	0.34	-0.04	0.32	0.06	Lazio	0.29	-0.17	0.27	0.22
Andalucia	0.27	-0.14	0.21	0.23	Liguria	0.41	0.12	0.23	0.02
Aquitaine	0.39	-0.19	0.27	0.35	Limousin	0.51	-0.22	0.23	0.57
Aragon	0.47	-0.15	0.24	0.41	Lombardia	0.31	-0.10	0.26	0.17
Asturias	0.46	-0.19	0.22	0.48	Lorraine	0.23	-0.12	0.31	0.07
Auvergne	0.57	-0.14	0.28	0.43	Madrid	0.32	0.04	0.27	0.00
Baden-Wurttemberg	0.35	-0.03	0.35	0.04	Marche	0.38	-0.10	0.26	0.21
Baleares	0.31	-0.21	0.29	0.28	Midi-Pyrenees	0.41	-0.10	0.28	0.23
Basilicata	0.50	0.08	0.32	0.05	Molise	0.55	-0.02	0.32	0.20
Basse-Normandie	0.50	-0.08	0.31	0.24	Murcia	0.28	-0.23	0.24	0.34
Bayern	0.43	0.02	0.35	0.04	Navarra	0.33	-0.43	0.29	0.81
Bourgogne	0.47	-0.05	0.30	0.19	Niedersachsen	0.26	-0.10	0.36	0.03
Bremen	0.32	-0.12	0.30	0.15	Nord-PasdeCalais	0.32	-0.05	0.34	0.04
Bretagne	0.38	-0.23	0.22	0.47	Nordrhein-Westfalen	0.20	-0.14	0.34	0.04
Calabria	0.40	0.00	0.25	0.12	Pais Vasco	0.27	-0.02	0.26	0.03
Campania	0.46	-0.03	0.25	0.20	PaysdelaLoire	0.45	-0.12	0.25	0.32
Canarias	0.43	0.02	0.21	0.15	Picardie	0.29	-0.12	0.30	0.12
Cantabria	0.52	-0.28	0.28	0.66	Piemonte	0.30	-0.17	0.28	0.22
Castilla-la Mancha	0.43	-0.42	0.29	0.90	Poitou-Charentes	0.49	-0.27	0.22	0.67
Castilla-Leon	0.52	-0.23	0.22	0.61	Prov-Alpes-C d'Azur	0.39	-0.11	0.30	0.20
Cataluna	0.36	-0.07	0.28	0.13	Puglia	0.47	0.02	0.25	0.16
Centre	0.46	0.04	0.28	0.09	Rheinland-Pfalz	0.24	-0.11	0.39	0.01
Champagne-Ard.	0.37	-0.10	0.31	0.16	Rhone-Alpes	0.39	-0.01	0.39	0.00
Com. Valenciana	0.24	-0.08	0.25	0.07	Rioja	0.39	-0.10	0.23	0.26
Emilia-Romagna	0.33	-0.18	0.26	0.29	Saarland	0.25	-0.11	0.38	0.02
Extremadura	0.65	-0.29	0.21	0.91	Sardegna	0.29	-0.02	0.28	0.02
Fr.-Venezia Giulia	0.44	-0.02	0.27	0.16	Schleswig-Holstein	0.28	-0.08	0.37	0.02
Franche-Comte	0.32	-0.09	0.29	0.12	Sicilia	0.29	-0.01	0.24	0.05
Galicia	0.50	-0.52	0.21	1.57	Toscana	0.33	-0.13	0.27	0.20
Hamburg	0.39	0.00	0.30	0.07	Trentino-Alto Adige	0.36	-0.14	0.32	0.20
Haute-Normandie	0.52	0.09	0.40	0.00	Umbria	0.25	-0.06	0.22	0.08
Hessen	0.47	0.05	0.35	0.04	Valle d'Aosta	0.23	-0.12	0.40	0.00
IledeFrance	0.58	0.00	0.32	0.20	Veneto	0.40	-0.05	0.25	0.17
Ireland	1.35	0.35	0.25	0.39	**MEAN (geo average)**	**0.40**	**-0.10**	**0.28**	**0.24**
					MEAN (normalized on 1980)			0.31	0.21
					MEAN (normalized on 2002)			0.26	0.27

Source: Authors calculations

Appendix B. Construction of Regional Capital Stocks

B1 Euros vs. PPS

In this version of the paper all data is presented in 1995 Euros. There are three reasons to decide against using PPS exchange rates in this study: (i) While purchasing power parities are appropriate to compare living standards, the economic interpretation of it is not straightforward when it comes to productivity studies. If we are willing to assume that a substantial part of output is brought out to an international market, it is not clear why the value of it should be adjusted according to the price level of the country of origin. In addition, regions with low price levels also have lower input costs and even though the value of capital can be adjusted according to PPS, labor input is not adjusted according to the lower salaries in low price regions. (ii) As large regional price differentials exists within countries, adjusting productivity numbers according to national PPS will induce as many new biases as they relief. PPP comparisons do give better comparisons of national living standards, but until regional PPS exist the adjustment may well give a distorted picture for example if high price regions in Northern Italy are given an unjust bonus according to national PPP. (iii) It is not completely clear how purchasing power factors are being adjusted over time in an increasingly integrated European Union.

B2 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, p. 178). In order to establish benchmarks for the capital stocks at the national level, a set of nationally comparable net capital stocks provided by Kamps (2001, 2004) were used. Kamps uses Perpetual Inventory Method (PIM) on investment series from 1860-2002 in order to construct a set of comparable national capital stocks that use the same size and geometric time profile of depreciation. From 1960 investment data are taken from official records collected by OECD, but for 1860-1959 artificial investment series were constructed for each country by assuming 4 percent increases annually up until the observed level in 1960 (Kamps: 2001, p. 7). However, as my series start in 1980, most of the capital stock is constructed from real data reported by OECD. Kamps data are reported in EUROS of 1995.

B3 Regional distribution of the national capital stocks

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. The regional share of the capital stock is very stable over time.

Italy:

Regional Italian gross capital stocks, estimated at the sectoral 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. The sum of the regional stocks was benchmarked against the total stock estimated by Kamps and the difference was less than 1 % yearly between 1994 and 2002.

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. When benchmarked against the total capital stock given by Kamps, the deviations of the sum of the regional stocks were less than 1%.

France:

Private regional capital stocks were estimated for the years 1985-1992 by Prud'Homme (1996) using local tax data, which should indicate an unbiased interregional distribution of the private capital stock, which is what matters for the present purpose. 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 SNCF. A problem with these series is that they do not do not constitute investments in education and health. However, the public capital stock of France amounted to 17-18 % of the total capital stock during 1980-2002, so in absence of better data, the cumulated sum of depreciation infrastructure investment will proxy for the regional share of public capital to the total public capital stock. The investments are depreciated linearly at 4 %. The regional shares of total public capital stocks are not sensitive to whether 2 % (50 year life time) or 4 % are used. Infrastructure (ports, highways, airports, railways, water investments, subways, trams) only contribute to 30 % of the capital stocks, whereas education, health and administration contribute to the other part.

In order to arrive at estimates for the *total* regional capital stock, 1992 is used as a benchmark. The total regional capitals stock of 1992 is calculated as the sum of the regional public capital stocks, as apportioned to the national public capital stock according to the relative weight calculated from the infrastructure investments and the private capital stock, calculated from the regional shares in Prud'Homme (1996) of the national private capital stock.

From the regional benchmark stocks of 1992, time series are calculated forward and backward using regional investment data from Cambridge Econometrics. Linear depreciation of 4% is used. When the sum of the regional capital stock is benchmarked against the total capital stock, measured by Kamps (2001), the difference between the two amounts to maximum 2,4 % difference (in 1980).

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