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Regional Disparities in the European Union:

Convergence and Agglomeration

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Abstract

Economic disparities between the regions of the European Union are of constant concern both for policy and economic research. In this paper we examine whether there are overlapping trends of regional development in the EU: overall convergence on the one hand and persistent or even increasing spatial concentration (agglomeration) on the other. Kernel density estimation, Markov chain analysis and cross-sectional regressions provide evidence that convergence of regional per-capita income in the EU15 has become considerably stronger in the 1990s. The reduction of income disparities, however, is a phenomenon between nations but not between regions within the EU countries. European integration (and possibly European regional policy) foster the catching-up of lagging countries but at the same time forces for agglomeration of economic activities tend to increase disparities within the EU member states. Obviously, the productive advantages of spatial proximity do not vanish in the knowledge economy.

JEL classification: C14, R11, R12

Keywords: Regional growth, agglomeration, Markov chains

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1 Introduction

In this paper we seek to draw a picture of aggregate regional disparities in Europe using two different approaches: nonparametric analysis of the regional distribution of per-capita income and its changes over the period from 1980 to 2000 and regression analysis of regional income differences controlling for agglomeration, country and spatial effects. We construct a typology of urban and non-urban regions for the EU15 in order to bring together two different perspectives on regional development: convergence and agglomeration. Empirical research on these two opposing forces is largely pursued in isolation of each other. This may prevent us from appropriately assessing regional disparities in Europe.

Political concerns about cohesion in the expanding and further integrating EU, the emergence of new theories of growth and economic geography, and improved data availability have sparked a wave of empirical research on regional development in Europe in the 1990s. One widely shared result is that the longstanding process of diminishing regional income disparities in Europe slowed down considerably in the 1980s, but it is still disputed whether convergence has regained momentum since then (see e.g. Barro and Sala-i-Martin 1995; Armstrong 1995; Neven and Gouyette 1995; Tondl 1999; López-Bazo et al. 1999; Boldrin and Canova 2001; Cuadrado-Roura 2001; Martin 2001; Maurseth 2001; Rodriguez-Pose and Fratesi 2002; Villaverde Castro 2002; LeGallo 2004, Gardiner et al. 2004). Many of these studies find that there is income convergence at the level of nations. However, regional disparities within the EU member states appear to persist or even to grow (see also Puga 2001; Giannetti 2002; Terrasi 2002; European Commission 2003, Cappelen et al. 2003). Moreover, it is widely accepted that spatial effects have an impact on the process of regional growth. Neighbouring regions tend to grow at similar speeds (see also Quah 1996a; Paci and Pigliaru 2002; Fingleton 2003). Finally, the traditional core-periphery pattern of manufacturing in Europe is weakening (Brülhart and Torstensson 1996; Midelfart-Knarvik et al. 2000; Midelfart-Knarvik and Overman 2002). This tends to work towards regional convergence. On the other hand, service industries appear to be shifting towards the centre of the EU (Brülhart and Traeger 2003), thus reinforcing divergence.

Regarding the spatial agglomeration of economic activities there are also a number of commonly agreed empirical facts (see e.g. Head and Mayer 2003; Combes and Overman 2003; Rosenthal and Strange 2005 for surveys). Productivity and wages are substantially higher in dense areas than in non-agglomerated regions (Rauch 1993; Ciccone and Hall 1996; Ciccone 2002; Glaeser et al. 1992; Glaeser 1998; Henderson 2003). This gap amounts to around one third. It is, however, not entirely attributable to externalities arising either from the co-location of specific industries (localisation economies) or from urban mass and diversity (urbanisation economies). About half the difference in aggregate income is the result of selection processes: High-income sectors, "white collar" activities and high skilled workers are disproportionately attracted to urban areas (Combes et al. 2004; Duranton and Puga 2004; Rice and Venables 2004). Generally, empirical studies on agglomeration effects are not directly informative about the change of these effects. But the similarity of estimates for different points in time or underlying periods suggests that agglomeration effects have not diminished over the last decades. In fact, they appear to have even increased (Duranton and Monastiriotis 2002; Hammond 2004).

During the 1990s there has been considerable debate on how to appropriately assess regional growth processes. Following the fundamental criticism of conventional β-convergence analysis brought forward by Quah (1993, 1996b) and others much of the empirical work turned to the observation of the whole regional income distribution and to interregional spillovers (neighbourhood effects). Another objection raised against many of the analyses on regional growth regards the definition of regions. Cheshire and Carbonaro (1995, 1996) propose functional (urban) regions rather than administrative units, which very often cut through intraregional socio-economic linkages. In the present study we combine elements of these discussions on the empirical assessment of regional growth in Europe. We first use nonparametric techniques to describe and analyse the shape and behaviour of the regional income distribution and the mobility over time of regions within this distribution. Second, we apply cross-sectional regression analysis to estimate the level and growth of aggregate per-capita income of the EU regions over the period from 1980 to 2000. To implement our notion of an income hierarchy according to types of regions a classification was developed ranging from large urban regions to rural areas. Our analyses are motivated mainly by two questions: Has absolute regional convergence in Europe regained pace in the course of further deepening of integration and intensification of cohesion policy in the 1990s? Has the spatial concentration of economic activities in Europe, and in particular the role of large urban areas, levelled off in the course of declining communication costs?

In the following sections we outline our empirical approach (section 2), describe our data basis and regional concept (section 3), present and discuss results (section 4) and draw some conclusions (section 5).

2 Empirical approach

Following the arguments that regressions may produce delusive results or, at least, miss important information contained in the data on regional growth (Quah 1993, 1996b; for a survey see Magrini 2005)[1] we proceed in two stages. We perform nonparametric analyses of the regional income distribution and its changes. With this approach, however, we cannot take into account in a systematic way potentially important features of the process of regional growth: national influences, agglomeration effects and spatial spillovers. Therefore, we complement these estimations by cross-sectional regression analyses where regional income is conditioned on country affiliation and settlement types of regions and where spatial effects are controlled for.

Kernel density estimation

In the first stage we apply kernel density estimation to derive univariate (two-dimensional) density functions of regional per-capita income for the years 1980, 1990 and 2000. It is well known that the results of density estimations depend both on the weighting function (kernel) used for calculating the densities at the various income levels and on the width of the data window sliding across the income distribution (see e.g. Silverman 1986, Fox 1990, Scott 1979 and 1992). As there are no definite criteria for optimal choices we experiment with a variety of kernels and bandwidths. While the Gaussian and Epanechnikov kernels lead to virtually identical results the cosine and Parzen kernels produce much rougher density functions for an intermediate range of bandwidths. But even in these latter cases the general shape of the income distribution among EU regions and a clear pattern of changes over time emerge behind the details. In the determination of bandwidths we follow Fox (1990) who proposes an "optimal" rule for a Gaussian kernel based on minimising the mean integrated squared error for an assumed normal distribution. If the (unknown) empirical density is not too different from normal density the rule works quite well. In order to check for over-smoothing we then reduce this bandwidth successively and our findings turn out to be fairly robust against these variations.

[1] Major objections are that regression analysis (1) only describes the average (i.e. "representative" region) behaviour and therefore neglects the dynamics of the entire income distribution, (2) beta-convergence found in regression analysis does not necessarily imply sigma-convergence, i.e. a reduction in the dispersion of regional in-

Markov chain analysis

Density estimation provides interesting information on the distribution of regional per-capita income and on changes in the shape of that distribution, but it reveals little about the way regions move up or down the income hierarchy. To evaluate the intra-distributional mobility of regions during the period observed we discretise the distribution into income classes and analyse the movements of regions between classes as a stochastic process. EU-relative GDP per capita in region *r* at time *t* is denoted y_r^t and a state space of *m* non-overlapping income classes is chosen (*i = 1, …, m*). If the sequence $\{y_r^0, y_r^1, \ldots\}$ satisfies the relation

$$P\{y_r^{t+1} = j \mid y_r^0 = i_0, y_r^1 = i_1, \ldots, y_r^{t-1} = i_{t-1}, y_r^t = i\} = P\{y_r^{t+1} = j \mid y_r^t = i\} = p_{ij} \quad (1)$$

for all classes, regions and points in time, then the process is called a discrete-time Markov chain (Kemeny and Snell 1976; Osaki 1992). The probability for a region to be in a certain income class *j* at time *t+1* depends only on its present position *i* (at time *t)* and is independent of the past history of the region (Markov property). The transition probabilities p_{ij} are assumed to be stationary (time-homogeneity) and the same for all regions (spatial homogeneity). Moreover, regions are assumed to move independent of each other (spatial independence).[2]

Under these conditions the process of transition between income classes can be described as

$$d_y^{t+1} = \boldsymbol{P} \cdot d_y^t \quad (2)$$

where the d_y denote the regional income distributions at time *t* and *t+1*, respectively, and ***P*** is the $m \times m$ matrix of transition probabilities p_{ij}. The elements of ***P*** are estimated by maximum likelihood, in effect, they represent the proportions of regions either remaining at their present level, indicated by the diagonal, or shifting up or down in the distribution. From the transition probability matrix a steady state distribution of regional incomes d_y^* can be derived if the

comes, (3) the "stylized" finding of 2 percent convergence of many studies could also be explained by the presence of unit roots in the time series.

[2] For a discussion and evaluation of the (rather restrictive) assumptions of Markov chain analysis see Fingleton (1997) and Bickenbach and Bode (2003). In particular, the assumption of spatial independence appears strong in view of empirical evidence for spatial interdependences in regional growth processes. However, with our definition of regions such spillovers are, at least partly, internalised (section 3). In addition, spatial growth dependencies are explicitly evaluated in the regression analysis (section 4).

Markov chain is ergodic.[3] This limiting distribution which is reached after s iterations (periods of time) is independent of the initial distribution of regional incomes at time $t = 0$:

$$\lim_{n \to \infty} d_y^t \cdot \boldsymbol{P}^s = d_y^* . \tag{3}$$

The speed of the system in approaching the stationary distribution is indicated by the second largest eigenvalue, λ_2, of the underlying transition matrix. The closer λ_2 is to unity the slower is this process. With λ_2 equal to zero the system has already reached its steady state distribution. As a practical measure, Shorrocks (1978) defined an asymptotic half life (hl):

$$hl = -\frac{\log 2}{\log|\lambda_2|} . \tag{4}$$

Multiplying hl by the number of years in the underlying periods of transition gives the time the system needs to cover half the distance to its limiting distribution.

Of course, the assumption that transition probabilities remain constant forever cannot claim any empirical relevance. Therefore, limiting distributions are in no way to be taken as long-term forecasts. They rather describe hypothetical situations that would occur if the regional mobility patterns observed for the past would persist infinitely. As with other analytical tools, limiting distributions inform us about the period under empirical consideration and (possibly) the near future but not about long-run developments.[4]

Analogous to kernel density estimation the results of Markov chain analysis depend in part on the way the income space is subdivided. The determination of discrete states (income classes) has to approximate the unknown density function that governed the empirical cross-sectional data. More classes tend to improve the approximation but the reliability of the estimated transition probabilities decreases in the number of observations per class. Fewer classes, on the other hand, may only roughly approximate the underlying density and substantial information on the intra-distributional dynamics, in particular at the extreme tails, may be lost. Straightforward choices for the discretising grid points such as quantiles or arbitrary percentage deviations from the mean (Quah 1993 and 1996b) can insure that all income classes (bins) are occupied by similar numbers of regions. This leads to variable bin widths and to a

[3] The Markov chain is ergodic if the transition matrix cannot be reduced, i.e., divided into closed subsets, and if all classes are aperiodic (p_{ij} are constant over time) and recurrent (regions are not absorbed by some income class, rather, they can return to their initial state in finite time).

loss of information about mobility patterns at the lower and, in particular, the upper end of the regional income hierarchy. Alternatively, Magrini (1999) proposes a procedure to optimise the width for a grid of equisized bins. The three methods discussed and tested there are based on the minimisation of either the mean integrated squared error or the absolute integrated error. In deriving optimal bin widths these approaches assume normality for the underlying density function but they also work for a range of non-normal samples.

In the present study we experimented with various ways of classifying the regional income distribution. While the basic results are very similar for all variants there are differences with respect to movements in the upper part of the income hierarchy. This is particularly relevant for us since we are interested both in convergence *and* agglomeration processes. In section 4 we report results derived from two different classifications: one constructed according to eight quantiles, providing more detail in the middle of the distribution, and the other proposed by Scott (1979) and discussed in Magrini (1999) leading to nine equisized income classes, providing more detail at the tails.[5] In both cases the classification is held constant over the entire period considered.

In order to base the estimation of transition probabilities on as large a number of observations as possible most applications of Markov chain analysis use annual transitions. This, however, is likely to be inconsistent with the assumption of time-independence (Markov property). For our study we chose 5-year intervals as transition periods. The resulting frequencies are pooled to form the transition probability matrix for the entire time span from 1980 to 2000. Since one of our hypotheses is that regional convergence has become stronger in the 1990s, i.e. that the transition behaviour of regions has changed around the middle of the period, we check for time-homogeneity using likelihood ratio and Pearson χ^2 tests as proposed by Bickenbach and Bode (2003).

Finally, we examine whether the transition behaviour of the whole sample is spatially homogeneous in the sense that it is representative for different types of regions. To be concrete, we estimate separate transition processes and limiting distributions for agglomerated and non-agglomerated areas.

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[4] Note that in the limiting (stationary) situation regions keep on moving according to p_{ij}, but the cross-sectional distribution does not change any more (Fingleton 1997).

[5] The estimate for the optimal bin width, h^*, according to Scott (1979) is $\hat{h}_n^* = 3.49 \cdot s \cdot n^{-1/3}$, where n is the sample size and s is the standard deviation.

Regression analysis of regional income disparities

Kernel density estimation and Markov chain analysis can provide valuable insights into the development of income disparities between EU regions, but there are clear limitations to these approaches regarding the characterisation of regional growth processes. In a second stage we therefore use regression analysis to assess the impact of national influences and agglomeration effects on regional growth. Country dummy variables capture the net effects of a number of factors at the national level:

- nation specific shocks and macro conditions,
- national institutions e.g. education, infrastructures and policies,
- national and subnational networks,
- country-specific preferences, cultures and behaviours,
- country-specific impacts of EU structural policies.

Settlement type dummy variables (see section 3 for a definition of types of regions) mirror the net influence of

- positive and negative effects of density,
- type of region specific infrastructures and human capital,
- high-performance modern cities and slow-growing declining industrial cities
- type of region specific impact of structural policy.

Since most of the explanatory variables, country and settlement type dummies, represent time-invariant characteristics of regions it is not possible to apply the standard approaches of panel data analysis. The influence of these broad categories of factors on regional income has to be evaluated in a cross-sectional setting. Nonetheless, for the purposes of the present study it is essential to allow for changes in patterns of regional growth during the two decades observed. We divide the entire period into four subperiods, thus performing not just one but a sequence of cross-sectional regressions. In order to reduce the impact of cyclical effects and data errors annual per-capita income is averaged for each subperiod (1980-1995, 1986-1990, 1991-1995, 1996-2000).

The estimations are based on two different specifications of the model, one for the level and one for the growth of per-capita income. Each of these specifications, in turn, is estimated in two versions, one without and one with country dummy variables. The level model is represented by the equation

$$\ln y_{it} = f(settlement\ type_i, [country_i])$$

where y denotes per-capita income, i refers to regions and t to subperiods. In the growth specification we add the lagged dependent variable to the right hand side to assess the change in regional disparities:

$$\ln y_{it} = \beta \ln y_{i,\,t-1} + f(\mathit{settlement\ type}_i,\ [\mathit{country}_i])\ .$$

Note that this is equivalent to the specification

$$\ln y_{it} - \ln y_{i,\,t-1} = (\beta - 1)\ln y_{i,\,t-1} + f(\mathit{settlement\ type}_i,\ [\mathit{country}_i])$$

with the growth rate of per-capita income, $\ln y_{it} - \ln y_{i,\,t-1}$, as dependent variable. We expect $\beta - 1$ to be significantly negative in case of convergence of regional incomes.

Although there is empirical evidence that the inclusion of country dummy variables greatly reduces the importance of spatial correlation (Fingleton 2003), spillovers across regional boundaries might still be a factor. Therefore, we report robust Lagrange multiplier (LM) tests for spatial error and spatial lag autocorrelations (Anselin 1988 and Anselin et al. 1996). Robustness refers to the presence of the other type of spatial correlation. The spatial diagnostic tests and spatial estimation require the definition of a distance weight matrix. We construct a binary matrix W_{ij}, so that an element w_{ij} of W_{ij} equals one if the distance (linear distance between regional centroids, see section 3) between region i and region j is less than a threshold distance (350 km), and zero otherwise. Other ranges (700 km and 1050 km) were also tested but the findings do not substantially differ from those with 350 km. The elements of W_{ij} are row-standardised, i.e. the sum of rows equals one.

We also check for heteroscedasticity and functional form misspecification using the White (1980) test. Because of the dummy variables we can only apply a modified form of the test where the squared dummy variables are excluded due to perfect collinearity. Since moderate heteroscedasticity shows up in almost all estimations robust t-values based on White's (1980) heteroscedasticity consistent standard errors are reported.

3 Data and regional delimitations

The choice of regional units and the availability of data are closely related issues. Clearly, there is a trade-off between the degree of regional disaggregation and the quantity of statistical information at hand. Most analyses on regional growth in Europe use NUTS1 or NUTS2 regions or a mixture of both concepts (prominent exceptions are Cheshire and Carbonaro 1996; Cheshire and Magrini 2000). However, the resulting units of observation are rather heterogeneous in terms of size and the degree of self containment. In general, NUTS1 regions are too large to capture truly regional growth processes whereas many NUTS2 regions are either too large or too small. The latter problem arises when cities are defined as NUTS2 regions and thereby are artificially separated from their economic hinterland. On the other hand many NUTS2 regions extend far beyond the reach of daily linkages, in particular commuting. In our regional concept we put priority on the formation of economically sensible regions. We start from the NUTS2 level, but in all cases where this delimitation appears either too narrow or too wide we turn to NUTS3 regions for a more appropriate definition of functionally integrated units of observation. In this respect, our approach is similar to the concept of Functional Urban Regions (Cheshire and Carbonaro 1996) but, unlike the latter, it is not restricted to urban areas. For lack of comprehensive information on commuting patterns the combination of statistical units is simply based on the distance from the centre of the respective local labour market. Generally, in our combined regions this distance does not exceed 80 kilometres, in most cases it is shorter.

Corresponding to our aim to analyse both patterns of regional growth and spatial concentration we construct a system of regions ranked according to the degree of urbanisation. We apply a four-level typology. The top group is formed by large agglomerations, i.e. regions with an urban core of more than half a million inhabitants and a total population of more than a million. At the second level we have smaller agglomerations with a population in the core between 300 000 and 500 000. The third group contains areas exhibiting a density of more than 150 inhabitants per square kilometre. Typically, these regions include one or two smaller cites with population between 100 000 and 300 000. Finally, the bottom group of our typology is formed by rural areas with a population density below 150 inhabitants per square kilometre. The number of regions assigned to each group is shown in Table A1 in the Appendix. In principal, urbanisation could also be captured by population density as a continuous variable. However, with NUTS 3 areas as smallest units available the result would be highly unsatisfying. For example, the density of the Spanish region Zaragoza is very low (48 inhabitants per square kilometre), but in fact the urban core of that region, the city of Zaragoza, has 540 000 inhabitants and is an important economic centre of northern Spain.

As a consequence of our choice of regions the empirical analysis is restricted to the set of data available at the NUTS3 level. We use population and income data from EUROSTAT REGIO database to analyse levels and growth of gross domestic product (GDP) per capita expressed in Purchasing Power Standards (pps) over the period from 1980 to 2000. There are two problems regarding time series data for this period. First, the introduction of the new

European System of National Accounts caused a break in the time series of GDP data in the middle of the 1990s. We chained the two sub-series (1980-1996 and 1995-2000) after equating the values of both series in 1995 and 1996. Second, for a number of countries that joined the EU during the period of observation regional data do not reach back as far as 1980. This applies to Sweden (1985), Denmark, Finland, Austria (all 1988) and East Germany (1991). Furthermore, Ireland and parts of the United Kingdom (Northern Ireland and Scotland) are first represented with their sub-regions in 1991.

Because of these gaps in the time series of GDP and population data we have to construct different data sets for the different stages of our empirical analysis. The analysis of the regional distribution of per-capita incomes requires a balanced panel with data for all regions and years. Here, countries with incomplete time series of regional data enter with their national values. This applies to five small countries of the EU. Similarly, Northern Ireland and Scotland are each taken as a whole. Eventually, we end up with data for 167 regions covering all of the EU15 except the eastern part of Germany.[6] The cross-sectional regressions are based on two different data sets, one containing 160 regions and covering the entire period from 1980 to 2000 and another with 206 regions covering the years from 1991 to 2000.

Our tests for spatial interdependencies are based on linear distances between regional centroids. The data were provided by the German Federal Office for Building and Regional Planning and adapted to our regional concept.

4 Results

Regional distribution of per-capita income

The estimated density functions characterising the distribution of GDP per capita across 167 European regions in the years 1980, 1990 and 2000 are shown in Figure 1. The distribution has undergone several notable changes during this time span. First, signs of bimodality at the lower tail apparent in 1980 and 1990 have largely disappeared. Obviously, European regions are not developing towards a twin-peak situation diagnosed by Quah (1996b) for the world economy and Magrini (1999) for the functional urban regions (FUR) of Europe. Second, the distribution has lost mass at the low end, particularly during the 1990s. Thus, the poorest regions are not inevitably trapped in their relative income position. Third, the upper tail has stretched out further during the two decades considered. The maximum EU relative income

[6] The region Groningen was dropped from all data sets. Groningen is the centre of the Dutch north sea gas industry and exhibited extreme changes of per-capita income in the 1980s, mainly due to fluctuations of gas prices.

was 2.1 (Luxemburg) in 2000 compared to 1.8 (Munich) in 1990 and 1.7 (Paris) in 1980.[7] Fourth, the number of regions with income around the average has continuously increased and in the 1990s the peak of the distribution has shifted from above to just below the average.

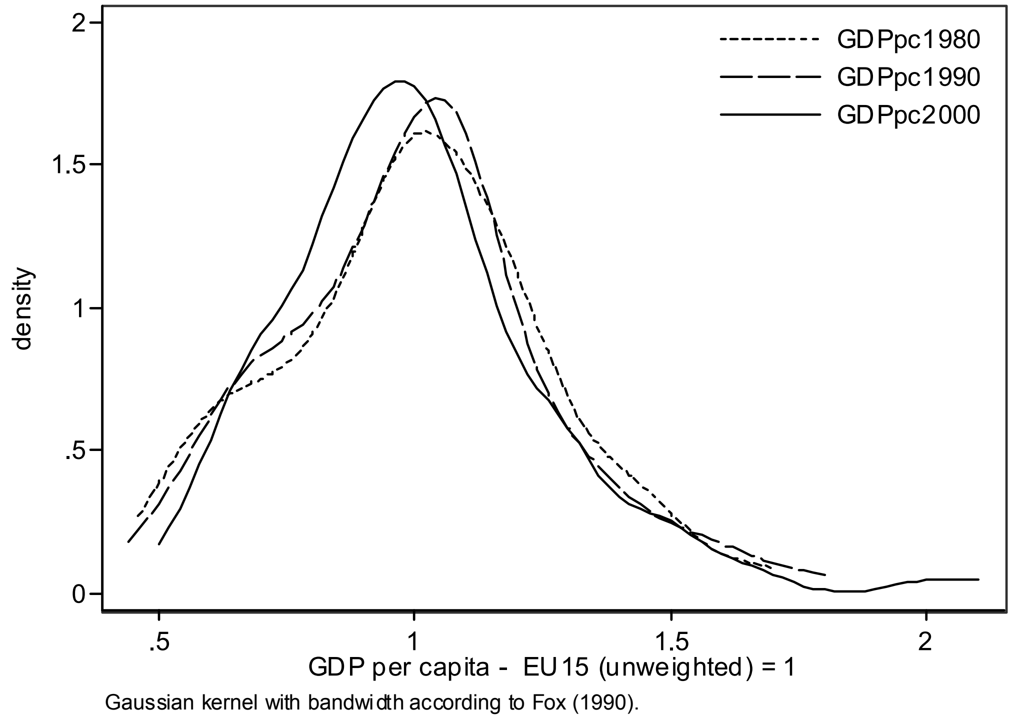

Fig. 1. Estimated density functions for 167 EU regions, EU relative per-capita income 1980, 1990 and 2000

The density functions presented in Figure 1 were estimated using the Gaussian kernel and "optimal" bandwidths as proposed by Fox (1990). More sensitive kernels and narrower bandwidths produce more sinuous curves but the general shape of the distribution and its change over time are the same. In particular, there is no over-smoothing of distant modes. So, the estimated densities can be regarded as valid representations of the underlying forces of regional development in the EU from 1980 to 2000. We observe tendencies both towards polarisation and equalisation, but the latter force appears to dominate.

The changes in the shape of the regional distribution of per-capita income are not the result of volatile movements. On average about three quarters of the regions stay in their income class over a period of 5 years (see transition probabilities in Tables A2 and A3 in the Appendix). Most regions that change their position move just one class up or down and hardly any region jumps across more than two classes. Almost all regions with initial income below 82% (Table A2) and 83% (Table A3) of the unweighted EU average have kept or improved

[7] Apart from the Italian region Trentino-Alto Adige, Luxemburg is the only non-agglomerated region in the top-10 group of the income hierarchy. Its extraordinary growth from 1980 to 2000 was almost exclusively driven by

their position, i.e. if anything, relatively poor regions become richer, not poorer. Many regions with above average incomes fell back in the ranking. A closer look at the regions involved shows that both national and regional factors are at work here. From 1980 to 2000 31 regions with just below or above average incomes dropped by more than 10 percentage points in the income hierarchy, 19 of these were French and 8 were West-German regions. Most of the 31 regions were either “old industrialised” or rural. Finally, the top of the income hierarchy is formed by a small and persistent group of urban areas. The leaders in 1980 (Paris, Brussels, Munich and Stuttgart) were still at the top (more than 50% above average) in 2000. Luxemburg, Frankfurt and Utrecht have joined this group during the period observed.[8] So, in 2000 the income of 7 regions exceeded the EU average by more than 50% compared to 4 regions in 1980.

The limiting distributions derived from the transition probability matrices for the entire time span from 1980 to 2000 are shown at to bottom of Tables A2 and A3 and in Figure 2. They indicate a clear tendency towards regional convergence. There is a pronounced mode near the average and the distributions are significantly tighter than the initial distributions. However, the speed of this process is extremely slow. The half-life time is 71 years for the quantile classification and 102 years for the Scott classification.

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the financial sector.

[8] A similar result was found by Magrini (1999) and Cheshire and Magrini (2000) for the periods 1979-1990 and 1978-1994, respectively, though their group of leading urban regions is somewhat different from ours.

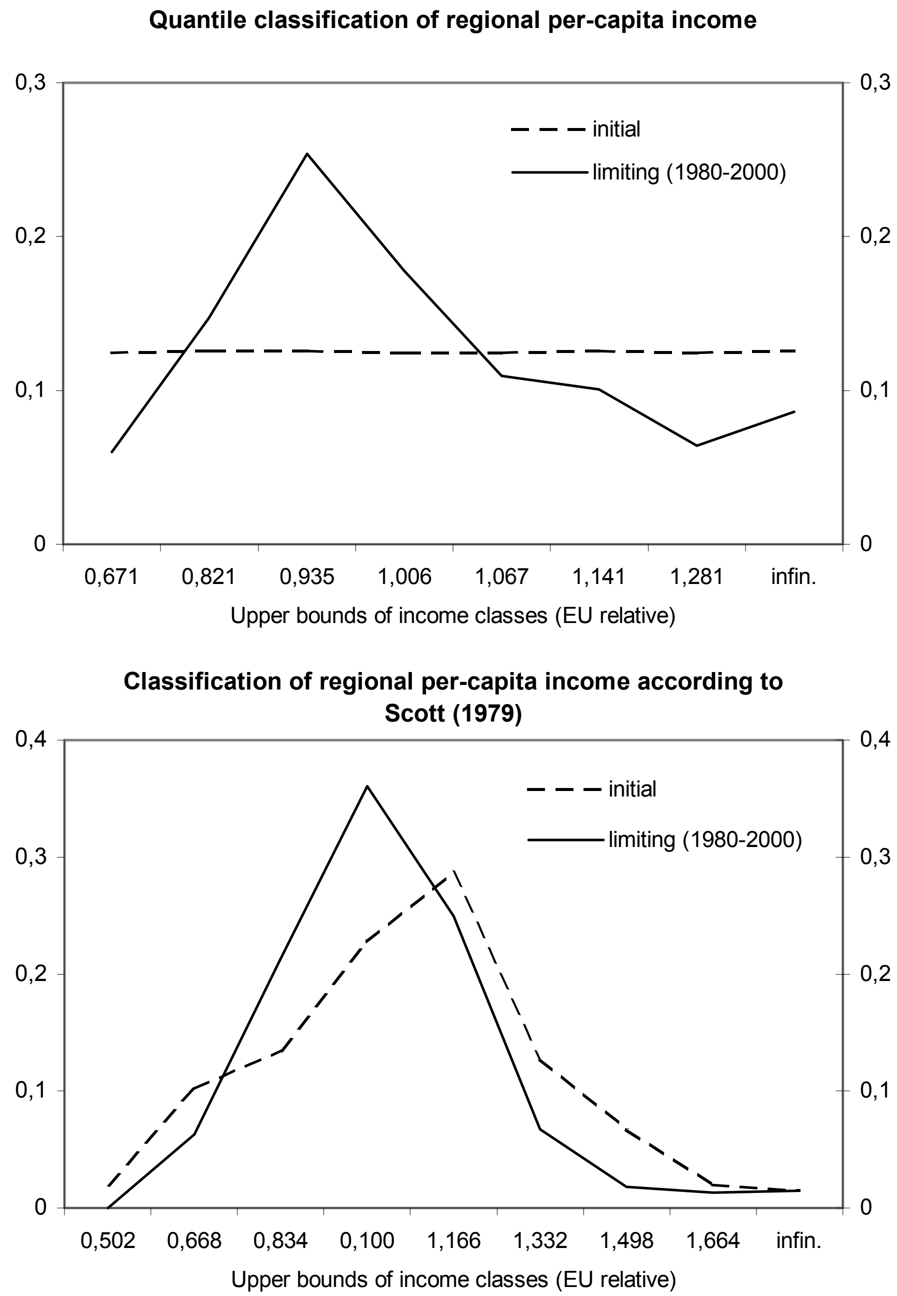


Fig. 2. Initial and limiting distributions of regional per-capita income

In order to check whether the empirical mobility pattern underlying these estimates has been stable during the two decades observed we formally test for structural breaks. The single transition matrices for five subperiods are consecutively compared to the matrix for the entire sample. On the basis of the test results we cannot reject the hypothesis of time-homogeneity (Table A4). But obviously, there are marked differences in the transition behaviour of regions between the 1980s and the 1990s. This is also reflected in the limiting distributions estimated separately for the two decades. The modes in the middle of the distributions derived from the transitions in the latter subperiod are much higher than for the 1980s (Figure A1 in the Appendix) and half-life times are shorter.[9] Of course, the partition of the whole time span implies that the number of observations for each subperiod is halved, too. With the classification of regional per-capita income according to Scott there are only a few cases left in the upper and lower classes, so, the reliability of the estimated transition probabilities and the related limiting distributions can be doubted. There is no easy way out of this problem, because increasing the number of observations requires shorter transition periods. That, in turn, increases the risk of violating the assumption of time independence (see section 2). As a compromise, we performed additional estimations using biennial instead of 5-year transitions. The results, based on 835 observations for each subperiod, are very similar to those presented in Figure A1.

While regional convergence within the EU has obviously regained momentum in the 1990s it is still slow. However, the implicit reference for such a judgement is perfect absolute convergence, irrespective of fundamental differences between regions. Is that a realistic (or desirable) scenario in the presence of localised externalities as described in section 1? Unless advantages of proximity are wiped out by information technology, firms and workers will continue to agglomerate. As a consequence, the duality of high-income urban areas and lower income non-urban areas will persist. In terms of Markov chain analysis that could mean that the assumption of spatial homogeneity is violated. If these two types of regions follow different trajectories with respect to their EU relative income the estimation of a common limiting distribution may be misleading. We control for different mobility patterns by running separate estimations for the 66 urban agglomerations (region types 1 and 2) and the 101 non-agglomerated areas (region types 3 and 4) using the same grid as for the all-region distribution. Again, the reliability of the estimated transition probabilities and limiting distributions is checked by additional estimations for biennial transitions.

The results of these separate estimations, summarised in Figure 3, show striking differences between types of regions with respect to intra-distributional mobility. Income disparities among non-urban areas are decreasing considerably. The majority of these regions are moving towards the average income and, again, that tendency appears to be stronger in the second half of the period. The limiting distributions based on the transition probabilities for the 1990s (not reported here) are much more concentrated in the middle than the distributions estimated for the whole time span from 1980 to 2000. Half-life times drop from 36 years to 22 years for the quantile classification and from 55 years to 15 years for the Scott classification.

[9] The estimated half-life times for the quantile classification of regional income are 82 years for the 1980s and 61 years for the 1990s. The corresponding figures for the Scott classification are 141 and 97 years.

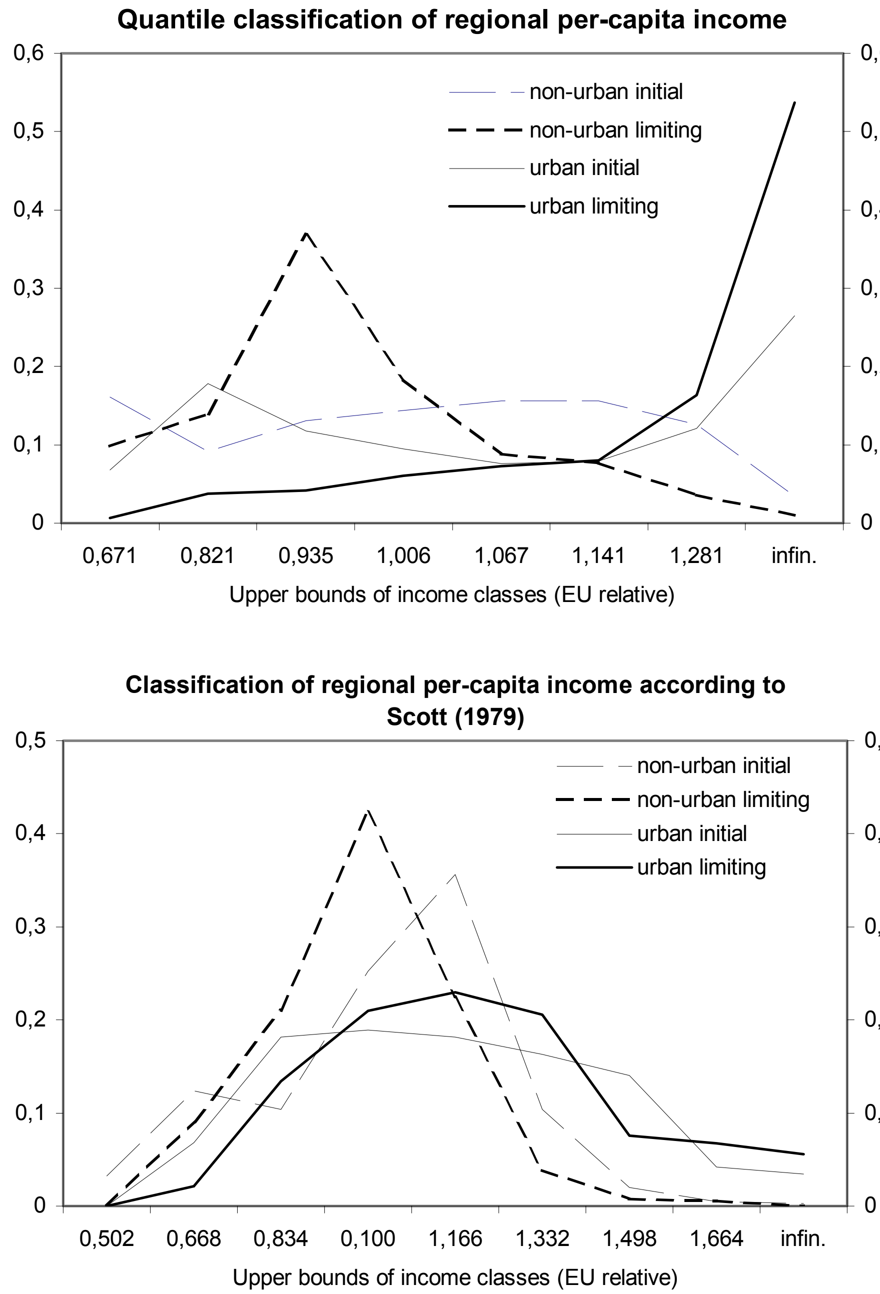


Fig. 3. Initial and limiting distributions for different types of regions

For urban areas the picture is less clear cut. Compared to the initial situation the limiting distribution shifts downwards for below-average incomes and upwards for above-average incomes. With the quantile grid this (hypothetical) long term outcome is particularly pronounced. Urban agglomerations converge towards the highest income class, but with a half-life time of more than a century this tendency is very weak (or mixed). The Scott classification where the upper tail of the distribution is represented in more detail leads to similar results. Generally, urban areas move further away from the average. They increasingly gather in high income classes, but that is no one-directional process. The drop of the limiting distribution at the third highest income class (between one third and one half above EU average) indicates that there is significant downward mobility among urban areas, too.

Overall, two preliminary conclusions can be drawn from the analysis of the regional distribution of per-capita income. First, regional disparities in aggregate economic activity are diminishing. This tendency was hardly existing in the 1980s, but stronger in the 1990s. Convergence occurred through catching-up of the poorest regions and relatively weak growth of many (erstwhile) richer regions. From a cohesion perspective these results allow for a more optimistic view than suggested by some other recent studies (Maza and Villaverde-Castro 2002; LeGallo 2004). Second, there is a force acting against convergence: agglomeration. The income gap between urban and non-urban areas is not shrinking. If anything, it tends to widen.

Regression results

As a starting point for the presentation of the regression results we use the growth model with lagged per-capita income and settlement type dummies as independent variables (Table A5). The estimations indicate that, first, regional income disparities have decreased and that this process of convergence has become sizeably stronger in the course of the period observed. Doubling the income level for the first half of the 1980s on average reduces the growth rate for the subperiod 1986-1990 by 4.1 percentage points, i.e. by around one tenth. The corresponding values for the 1990s are 7.5 percentage points and around one third. Second, urban agglomerations, in particular large metropolitan areas, not only show higher income levels than rural regions, they also grow somewhat faster. This tendency levelled off in the first half of the 1990s but regained strength thereafter.

Of course, this is a very crude model that "explains" only a small part of the variation in regional per-capita income. The jump of R^2 from 0.16 in the case 160 regions to 0.365 for 206 regions is mainly due to the inclusion of East Germany. Nonetheless, these estimations confirm the results of the non-parametric analyses presented in the previous subsection.

Findings change substantially, however, as soon as national effects are considered. Except for the first half of the 1990s convergence disappears completely when country dummies are included as independent variables (Table 1). Obviously, the reduction of income disparities is a process between member states of the EU, not between regions within these states. Moreover, with national effects accounted for, growth of per-capita income of urban areas is no longer significantly higher than that of rural regions. Closer inspection of the data reveals that the growth performance of urban agglomerations compared to rural regions tends to improve during periods of relatively strong national growth, and vice versa. Estimates for the *level* of per-capita income show that the metropolitan areas at the least maintain their lead on non-metropolitan regions (Table A6 in the Appendix). Thus the lack of regional convergence within nations is essentially due to the persistent strength of agglomeration economies attracting high-income activities to urban areas. This interpretation is forcefully corroborated by evidence on the development of the spatial division of labour (Duranton and Puga 2004; Bade et al. 2004).

Table 1. Cross-sectional regression results (OLS) – Growth of per-capita income (y) with country dummy variables

	Dep. var.: $\ln y_t - \ln y_{t-1}$							
	t: 1986-1990[a]		t: 1991-1995[a]		t: 1996-2000[a]		t: 1996-2000[b]	
	Coeff.	*t-value*	*Coeff.*	*t-value*	*Coeff.*	*t-value*	*Coeff.*	*t-value*
Intercept	0.364***	(8.33)	0.344***	(8.32)	0.145***	(2.97)	0.230***	(4.20)
$\ln y_{t-1}$	0.002	(0.09)	-0.028*	(-1.69)	0.021	(1.20)	-0.011	(-0.54)
Large urban areas	0.011	(0.99)	-0.000	(-0.03)	0.006	(0.85)	0.011	(1.46)
Small urban areas	0.010	(0.92)	-0.004	(-0.59)	0.006	(0.96)	0.010	(1.72)
Intermediate regions	0.009	(0.76)	-0.010	(-1.05)	-0.006	(-0.86)	0.003	(0.43)
Austria	—	—	—	—	—	—	0.023*	(1.94)
Belgium	-0.015	(-0.91)	0.033***	(3.35)	-0.018**	(-2.17)	-0.019**	(-1.99)
Germany	-0.001	(-0.09)	0.026***	(3.04)	-0.042***	(-5.07)	-0.041***	(-4.81)
Denmark	—	—	—	—	—	—	0.059***	(2.78)
Spain	0.027*	(1.70)	0.027***	(3.34)	0.018**	(1.98)	0.011	(1.16)
Finland	—	—	—	—	—	—	0.069***	(4.83)
France	-0.041***	(-4.67)	-0.049***	(-7.15)	-0.051***	(-5.77)	-0.050***	(-5.92)
Greece	-0.016	(-0.69)	0.012	(0.69)	0.074***	(3.45)	0.060***	(2.65)
Ireland	—	—	—	—	—	—	0.236***	(11.69)
Luxemburg	0.187***	(14.61)	0.139***	(12.60)	0.085***	(6.74)	0.096***	(7.62)
Netherlands	-0.000	(-0.02)	0.001	(0.08)	0.061***	(4.67)	0.059***	(4.11)
Portugal	0.062**	(2.41)	0.066**	(2.07)	0.069***	(4.14)	0.056***	(3.36)
Sweden	—	—	—	—	—	—	-0.008	(-0.67)
United Kingdom	0.026**	(2.39)	-0.053***	(-6.02)	0.028***	(2.82)	0.018*	(1.80)
East Germany	—	—	—	—	—	—	0.205***	(7.10)
Number of regions	160		160		160		206	
R-squared	0.322		0.564		0.634		0.757	

Robust t statistics in parentheses; * significant at 10%, ** significant at 5%, *** significant at 1%; [a]160 regions, [b]206 regions.
Note: reference categories are Italy (for country effects) and rural regions (for settlement type effects).

The estimated coefficients of the country dummy variables are all highly plausible in light of the growth performance of European nations since 1980. Most of the countries show stable development paths relative to the reference nation, Italy.[10] Contrary to the first impression from Table 1, Germany is no exception to this general picture. Both the strong growth of per-capita income at the beginning of the 1990s and the weak growth thereafter are largely due to an external shock, the German unification. Southern European countries are almost constantly catching up and Luxemburg is pressing further ahead. The only country with pronounced fluctuations of relative growth during the two decades observed is the UK.[11] There is somewhat more fluctuation at the regional level, but generally regions too do not change their growth performance erratically.

Table A7 in the Appendix reports robust Lagrange multipliers from the spatial error and the spatial lag model for the last subperiod, 1996-2000. The results for the other subperiods are very similar. These tests indicate significant interdependencies between regions in terms of per-capita income. However, when national effects are considered this is only true for the level but not for the growth of income. This is in line with other evidence on the issue: Fingleton (2003) states that the inclusion of country dummy variables eliminates spatial autocorrelation in the growth regression, Eckey et al. (2003) find significant growth spillovers between European regions, but not across national borders.

Our cross-sectional growth model with the lagged level of per-capita income, agglomeration dummies and country dummies as independent variables explains a large part of the variation in regional growth of per-capita income. The estimation results confirm and extend the information gained from the non-parametric analyses. Although we deal with broad categories of factors rather than with specific growth determinants (see e.g. Cheshire and Magrini 2000) our findings can contribute to a more realistic assessment of the process of regional development in Europe and of policy options.

5 Conclusions

Disparities in per-capita income between the regions of the EU15 are decreasing. This process of (absolute) convergence was interrupted in the first half of the 1980s but regained strength thereafter. On the basis of our aggregate empirical analyses we cannot determine if and to what extent the observed reduction of disparities is the result of neoclassical convergence through capital deepening and factor mobility, or technological convergence through

[10] Italy was chosen as reference category because it developed very similar to the EU15 as a whole. The Italian per-capita income remained slightly above the average over the entire period observed.
[11] Sweden, Denmark and, in particular, Finland exhibited also heavy fluctuations in their macro-economic development, but the regions of these countries (as with Austria and Ireland) could only be included in the regression analysis for the 1990s.

faster diffusion of innovations and imitation, or New Economic Geography convergence induced by very low transactions costs, or, not least, EU regional and cohesion policy. What we can say, however, is that the reduction of income disparities is a phenomenon between nations not between regions within the EU countries. National events, networks, institutions, infrastructures, policies and macro-economic conditions determine the growth path of countries and their regions, even if there is considerable regional variation on this path.

A major cause for that variation is the fact that urban areas keep, and in many cases even improve, their position at the top of the regional income hierarchy. Again, we cannot distinguish between possible single factors behind this tendency: faster growth of productivity in urban agglomerations due to localised dynamic spillovers and R&D infrastructures or selection of specific economic activities (sectors and functions) into specific types of regions following pecuniary or pure externalities. In any case, the regional economic structure of EU countries is persistently shaped by agglomeration economies attracting high-income activities to urban areas. The internet and knowledge society may increasingly become weightless, but there is no indication that it is becoming spaceless, too.

Low overall convergence rates cannot be taken as evidence of weak economic coherence of the EU. In fact, there is considerable convergence between the member states. European integration (and possibly European regional and cohesion policy) foster the catching-up of lagging countries but at the same time forces for agglomeration of economic activities tend to increase disparities within countries. EU and national interventions to counter these forces for the sake of more convergence would almost certainly come at the expense of economic growth.

References

Anselin L (1988) Spatial Econometrics: Methods and Models, Kluwer Academic Publishers, London.

Anselin L, Bera AK, Florax R, Yoon MJ (1996) Simple diagnostic tests for spatial dependence. Regional Science and Urban Economics 26: 77–104.

Armstrong H (1995) Convergence among regions of the European Union 1950-1990. Papers in Regional Science 74: 143-152.

Bade F-J, Laaser C-F, Soltwedel R (2004) Urban Specialization in the Internet Age - Empirical Findings for Germany. Kiel Working Paper 1215.

Barro R, Sala-i-Martin X (1995) Economic Growth. McGraw-Hill, New York.

Bickenbach F, Bode E (2003) Evaluating the Markov Property in Studies of Economic Convergence. International Regional Science Review 26: 363-392.

Boldrin M, Canova F (2001) Inequality and convergence in Europe’s regions: reconsidering European regional policies. Economic Policy 32: 207-253.

Brülhart M, Torstensson J (1996) Regional Integration, Scale Economies and Industry Location in the European Union. CEPR Discussion Paper 1435.

Brülhart M, Traeger R (2003) An Account of Geographic Concentration Patterns in Europe. Paper presented at the 2003 ERSA Congress, Jyvaskyla (Finland).

Canova F, Marcet A (1995) The Poor Stay Poor: Non-Convergence Across Countries and Regions. CEPR Discussion Paper 1265.

Cappelen A, Castellacci F, Fagerberg J, Verspagen B (2003) Regional Disparities in Income and Unemployment in Europe. In: Fingleton B (ed): European Regional Growth. Springer.

Cheshire P, Carbonaro G (1995) Convergence – Divergence in Regional Growth Rates: An Empty Black Box? In: Armstrong HW, Vickerman RW (eds) Convergence and Divergence Among European Regions. Pion, London.

Cheshire P, Carbonaro G (1996) Urban Economic Growth in Europe: Testing Theory and Policy Prescriptions. Urban Studies 33: 1111-1128.

Cheshire P, Magrini S (2000) Endogenous Processes in European Regional Growth: Convergence and Policy. Growth and Change 31 (Fall): 455-479.

Ciccone A (2002) Agglomeration effects in Europe. European Economic Review 46: 213-227.

Ciccone A, Hall RE (1996) Productivity and the density of economic activity. American Economic Review 86: 54-70.

Combes P-P, Overman HG (2003) The Spatial Distribution of Economic Activity in the European Union. CEP Discussion Paper 587.

Combes P-P, Duranton G, Gobillon L (2004) Spatial Wage Disparities: Sorting Matters! CEPR Discussion Paper 4240.

Cuadrado-Roura JR (2001) Regional convergence in the European Union: From hypothesis to the actual trends. Annals of Regional Science 35: 333-356.

Duranton G, Monastiriotis V (2002) Mind the Gaps: The Evolution of Regional Earnings Inequalities in the U.K., 1982-1997. Journal of Regional Science 42: 219-256.

Duranton G, Puga D (2004) From sectoral to functional urban specialisation. CEPR Discussion Paper 2971.

Eckey H-F, Kosfeld R, Türck M (2003) Intra- und internationale Spillover-Effekte zwischen den EU-Regionen. Volkswirtschaftliche Diskussionsbeiträge der Universität Kassel, Nr. 50.

European Commission, DG Regional Policy (2003): Second progress report on economic and social cohesion. Brussels.

Fingleton B (1997) Specification and Testing of Markov Chain Models: An Application to Convergence in the European Union. Oxford Bulletin of Economics and Statistics 59: 385-403.

Fingleton B (2003) Introduction. In: Fingleton B (ed): European Regional Growth. Springer.

Fox J (1990) Describing Univariate Distributions. In: Fox J, Long JS (eds): Modern Methods of Data Analysis. Sage Publications, Newbury Park.

Gardiner B, Martin R, Tyler P (2004) Competitiveness, Productivity and Economic Growth across the European Regions. Regional Studies 38: 1045-1067.

Giannetti M (2002) The effects of integration on regional disparities: Convergence, divergence or both? European Economic Review 46: 539-567.

Glaeser E, Kallal H, Scheinkman J, Shleifer A (1992) Growth in Cities. Journal of Political Economy 100: 1126-1152

Glaeser E (1998) Are Cities Dying? Journal of Economic Perspectives 12: 139-160.

Hammond GW (2004) Metropolitan/non-metropolitan divergence: A spatial Markov chain approach. Papers in Regional Science 83: 543-563.

Head K, Mayer T (2003) The Empirics of Agglomeration and Trade. CEPR Discussion Paper 3985.

Henderson JV (2003) Marshall's economies. Journal of Urban Economics 53: 1-28.

LeGallo J (2004) Space-Time Analysis of GDP Disparities among European Regions: A Markov Chains Approach. International Regional Science Review 27: 138-163.

López-Bazo E, Vayá E, Mora AJ, Surinach J (1999) Regional economic dynamics and convergence in the European Union. Annals of Regional Science 33: 343-370.

Magrini S (1999) The evolution of disparities among the regions of the European Union. Regional Science and Urban Economics 29: 257-281.

Magrini S (2005) Regional (Di)Convergence. In: Henderson V, Thisse JF (eds) Handbook of Regional and Urban Economics, Volume 4. North-Holland.

Martin R (2001) EMU versus the regions? Regional convergence and divergence in Euroland. Journal of Economic Geography 1: 51-80.

Maza A, Villaverde J (2004) Regional disparities in the EU: mobility and polarization. Applied Economics Letters 11: 517-522.

Maurseth PB (2001) Convergence, geography and technology. Structural Change and Economic Development 12: 247-276.

Midelfart-Knarvik KH Overman HG (2002) Delocation and European integration. Economic Policy, October: 322-359.

Midelfart-Knarvik KH Overman HG Redding S, Venables A (2000) The Location of European Industry. European Commission, DG Economic and Financial Affairs, Economic Papers 142.

Neven D, Gouyette C (1995) Regional Convergence in the European Community. Journal of Common Market Studies 33: 47-65.

Osaki S (1992) Applied Stochastic System Modeling. Springer, Berlin.

Paci R, Pigliaru F (2002) Technological Diffusion, Spatial Spillovers and Regional Convergence in Europe. In: Cuadrado-Roura JR, Parellada M (eds) Regional Convergence in the European Union. Springer, Berlin.

Puga D (2001) European Regional Policies in Light of Recent Location Theories. CEPR Discussion Paper 2767.

Quah D (1993) Empirical cross-section dynamics in economic growth. European Economic Review 37: 426-434.

Quah D (1996a) Regional convergence clusters across Europe. European Economic Review 40: 951-958.

Quah D (1996b) Empirics for economic growth and convergence. European Economic Review 40: 1353-1375.

Rauch JE (1993) Productivity gains from geographic concentration of human capital: Evidence from the cities. Journal of Urban Economics 34: 380-400.

Rice P, Venables AJ (2004) Spatial Determinants of Productivity: Analysis for the Regions of Great Britain. CEP Discussion Paper 642.

Rodríguez-Pose A, Fratesi U (2002) Unbalanced development strategies and the lack of regional convergence in the EU. Paper presented to the 2002 ERSA Congress, Dortmund (Germany).

Rosenthal S, Strange W (2005) Evidence on the nature and sources of agglomeration economies. In: Henderson V, Thisse J-F (eds) Handbook of Regional and Urban Economics, volume 4, North-Holland, Amsterdam (forthcoming).

Scott DW (1979) Optimal and data-based histograms. Biometrika 66: 605-610.

Scott DW (1992) Multivariate Density Estimation: Theory, Practice, and Visualization. John Wiley & sons, New York.

Shorrocks AF (1978) The measurement of mobility. Econometrica 46: 1013-1024.

Silverman, B. W. (1986): Density Estimation for Statistics and Data Analysis. Chapman & Hall, London.

Terrasi M (2002) National and Spatial Factors in EU Regional Convergence. In: Cuadrado-Roura JR, Parellada M (eds) Regional Convergence in the European Union. Springer, Berlin.

Tondl G (1999) The changing pattern of regional convergence in Europe. Jahrbuch für Regionalwissenschaft 19: 1-33.

Villaverde Castro J (2002) Regional convergence, polarisation and mobility in the European Union 1980-1996. Paper presented to the 2002 ERSA Congress, Dortmund (Germany).

White H (1980) A Heteroscedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity. Econometrica 48: 817-838.

Appendix

Table A1. Number of observed regions by settlement type and category of analysis

Type of region	Non-parametric analysis 1980-2000	Cross-sectional regressions 1980-2000	Cross-sectional regressions 1991-2000
(1) Large urban areas	35	35	42
(2) Small urban areas	31	31	36
(3) Intermediate regions	30	30	32
(4) Rural regions	71	64	96
Total	167	160	206

In the non-parametric analyses nations and parts of nations for which regional data were not available for the entire period from 1980 to 2000 are assigned to rural regions (Sweden, Finland, Denmark, Austria, Ireland, Northern Ireland, Scotland). The data set for the cross-sectional regressions covers 160 regions for the whole period and 206 regions for the years from 1991 to 2000. East Germany is not included in the data for the non-parametric analyses, the Dutch region Groningen is not represented at all.

Table A2. Transition probability matrix for 167 EU regions 1980-2000, 5-year transition periods, quantile classification of per-capita incomes

Income Classes	Obser-vations	Upper Bounds	Transition Probabilities							
			0.671	0.821	0.935	1.006	1.067	1.141	1.281	∞
1	83	0.671	0.795	0.205						
2	84	0.821	0.083	0.738	0.167	0.012				
3	84	0.935		0.095	0.690	0.202	0.012			
4	83	1.006		0.012	0.289	0.482	0.157	0.048	0.012	
5	83	1.067			0.024	0.337	0.446	0.193		
6	84	1.141				0.012	0.274	0.560	0.155	
7	83	1.281				0,012	0.036	0.229	0.627	0.096
8	84	∞							0.071	0.929
Initial Distribution			0.124	0.126	0.126	0.124	0.124	0.126	0.124	0.126
Limiting Distribution			0.060	0.147	0.254	0.178	0.110	0.101	0.064	0.086

Due to rounding, probabilities and distributions do not always add up exactly to unity.
The number of observations is the total sum of regions that have ever been in the respective class over the 4 transition periods. The upper bounds of the income classes indicate regional per-capita income relative to the unweighted EU average. The bounds were determined so that the total of 668 observations are subdivided into 8 income classes with equal frequencies (8 quantiles).

Table A3. Transition probability matrix for 167 regions 1980-2000, 5-year transition periods, classification of per-capita incomes according to Scott (1979)

Income Classes	Obser-vations	Upper Bounds	Transition Probabilities								
			0.502	0.668	0.834	1.000	1.166	1.332	1.498	1.664	∞
1	13	0.502	0.769	0.231							
2	68	0.668		0.735	0.265						
3	90	0.834		0.078	0.744	0.178					
4	152	1.000			0.105	0.783	0.105	0.007			
5	192	1.166				0.161	0.781	0.057			
6	85	1.332					0.247	0.706	0.047		
7	45	1.498						0.178	0.711	0.111	
8	13	1.664							0.154	0.615	0.231
9	10	∞								0.200	0.800
Initial Distribution			0.019	0.102	0.135	0.228	0.287	0.127	0.067	0.019	0.015
Limiting Distribution			0.000	0.063	0.213	0.360	0.250	0.067	0.018	0.013	0.015

The bounds of income classes were calculated according to the Scott (1979) criterion applied to the average of the cross-sectional distributions for the initial years of the 4 transition periods (1980, 1985, 1990 and 1995).
For more notes see Table A2.

Table A4. Test of time-homogeneity of transition probabilities for 167 EU regions, biennial transitions: Contributions of subperiods to the Pearson (Q) and Likelihood Ratio (LR) test statistics

Subperiods	df	Q	probQ	LR	probLR
1980-1984	20	16.367	0.694	16.091	0.711
1984-1988	20	18.382	0.562	16.964	0.655
1988-1992	20	19.120	0.514	16.923	0.658
1992-1996	20	8.557	0.987	10.007	0.968
1996-2000	20	10.915	0.948	14.947	0.779
Total	80	73.341	0.687	74.931	0.639

Note: The degrees of freedom are not corrected for restrictions across subsamples, therefore they do not add up to the total. Very kindly, Eckhardt Bode provided his computer programme for the test (see also Bickenbach and Bode 2003).

Table A5. Cross-sectional regression results (OLS) – Growth of per-capita income (no dummy variables for nations)

	Dep. var.: $\ln y_t - \ln y_{t-1}$							
	t: 1986-1990[a]		t: 1991-1995[a]		t: 1996-2000[a]		t:1996-2000[b]	
	Coeff.	*t-value*	*Coeff.*	*t-value*	*Coeff.*	*t-value*	*Coeff.*	*t-value*
Intercept	0.441***	(12.58)	0.424***	(9.81)	0.394***	(6.98)	0.413***	(7.81)
$\ln y_{t-1}$	-0.041**	(-2.41)	-0.065***	(-3.64)	-0.075***	(3.59)	-0.077***	(-3.98)
Large urban areas	0.035***	(3.24)	0.018	(1.62)	0.032***	(3.22)	0.026**	(2.26)
Small urban areas	0.025**	(2.33)	0.014	(1.63)	0.025**	(2.41)	0.012	(1.30)
Intermediate regions	0.032***	(2.63)	0.018	(1,53)	0.004	(0.38)	-0.005	(-0.58)
Dummy East Germany	-	-	-	-	-	-	0.135***	(5.81)
Number of regions	160		160		160		206	
R-squared	0.082		0.106		0.160		0.365	

Robust t statistics in parentheses; * significant at 10%, ** significant at 5%, *** significant at 1%; [a] 160 regions, [b] 206 regions.
Note: the reference category for settlement types are rural regions (type 4).

Table A6. Cross-sectional regression results (OLS) – Level of per-capita income (y) with country dummy variables

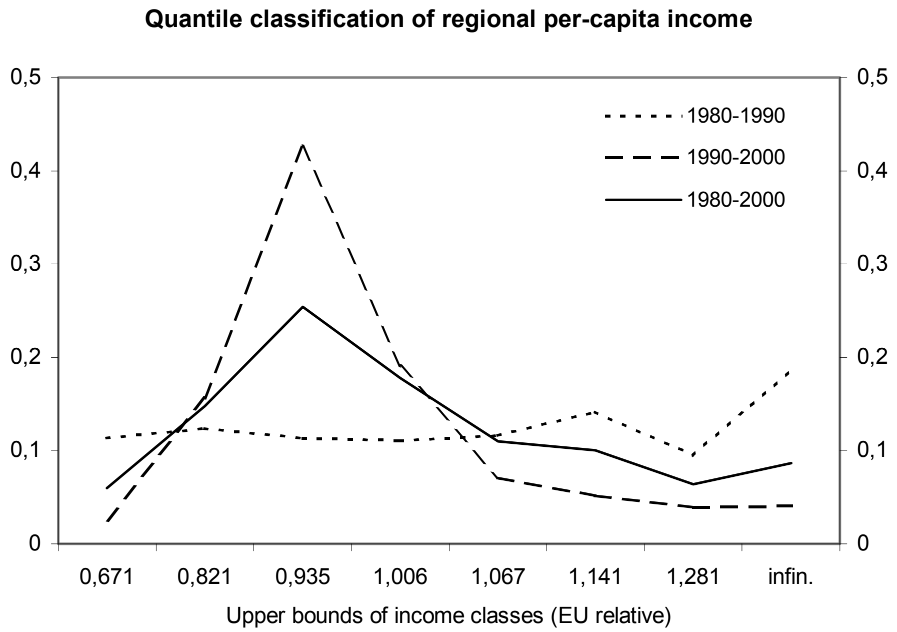
	Dep. var.: $\ln y_t$											
	t: 1980-1985[a]		t: 1986-1990[a]		t: 1991-1995[a]		t: 1996-2000[a]		t: 1991-1995[b]		t: 1996-2000[b]	
	Coeff.	*t-value*	*Coeff.*	*t-value*	*Coeff.*	*t-value*	*Coeff.*	*t-value*	*Coeff.*	*t-value*	*Coeff.*	*t-value*
Intercept	2.062***	(32.30)	2.430***	(37.01)	2.705***	(41.12)	2.908***	(44.65)	2.698***	(41.49)	2.900***	(44.93)
Large urban areas	0.205***	(4.84)	0.217***	(4.82)	0.211***	(4.65)	0.221***	(4.73)	0.231***	(6.01)	0.240***	(6.20)
Small urban areas	0.071	(1.65)	0.081*	(1.88)	0.075*	(1.75)	0.082*	(1.87)	0.085**	(2.31)	0.094**	(2.50)
Intermediate regions	0.054	(1.61)	0.063*	(1.71)	0.051	(1.40)	0.046	(1.20)	0.046	(0.05)	0.049	(1.47)
Austria	—	—	—	—	—	—	—	—	0.094	(1.02)	0.116	(1.33)
Belgium	-0.016	(-0.18)	-0.031	(-0.36)	0.003	(0.04)	0.015	(0.16)	0.003	(0.04)	-0.015	(-0.17)
Germany	0.110*	(1.84)	0.110*	(1.75)	0.133**	(2.09)	0.093	(1.42)	0.136**	(2.12)	0.094	(1.42)
Denmark	—	—	—	—	—	—	—	—	0.154**	(2.03)	0.211***	(3.15)
Spain	-0.306***	(-4.14)	-0.280***	(-3.73)	-0.245***	(-3.30)	-0.232***	(-3.07)	-0.226***	(-3.28)	-0.233***	(-3.05)
Finland	—	—	—	—	—	—	—	—	-0.012	(-0.12)	0.057	(0.56)
France	0.112*	(1.71)	0.071	(1.05)	0.020	(0.29)	-0.031	(-0.46)	0.024	(0.35)	-0.027	(-0.40)
Greece	-0.457***	(-6.31)	-0.475***	(-6.26)	-0.449***	(-5.96)	-0.385***	(-5.00)	-0.445***	(-5.89)	-0.380***	(-4.91)
Ireland	—	—	—	—	—	—	—	—	-0.172*	(-1.81)	0.066	(0.62)
Luxemburg	0.245***	(4.22)	0.433***	(7.12)	0.560***	(9.11)	0.657***	(10.23)	0.572***	(9.20)	0.662***	(10.33)
Netherlands	0.017	(0.24)	0.016	(0.24)	0.017	(0.24)	0.078*	(1.04)	0.017	(0.24)	0.076	(1.01)
Portugal	-0.578***	(-7.34)	-0.517***	(-5.94)	-0.436***	(-5.13)	-0.376***	(-4.56)	-0.435***	(-5.16)	-0.374***	(-4.58)
Sweden	—	—	—	—	—	—	—	—	0.064	(0.99)	0.056	(0.85)
United Kingdom	-0.087	(-1.32)	-0.061	(-0.86)	-0.112	(-1.58)	-0.086	(-1.19)	-0.093	(-1.30)	-0.075	(-1.04)
East Germany	—	—	—	—	—	—	—	—	-0.581***	(-14.98)	-0.370***	(-13.28)
Number of regions	160		160		160		160		206		206	
R-squared	0.678		0.652		0.631		0.566		0.652		0.584	

Robust t statistics in parentheses; * significant at 10%, ** significant at 5%, *** significant at 1%; [a] 160 regions, [b] 206 regions.
Note: reference categories are Italy (for country effects) and rural regions (for settlement type effects).

Table A7. Spatial diagnostic tests for selected models from Tables 1, A5 and A6 (distance 350 km, row standardised binary weight matrix)

	Growth 1996/2000 – 1991/1995 without country dummy variables				Growth 1996/2000 – 1991/1995 with country dummy variables				Level 1996/2000 with country dummy variables			
	Statistic	*p-value*	*Statistic*	*p-value*	*Statistic*	*p-value*	*Statistic*	*p-value*	*Statistic*	*p-value*	*Statistic*	*p-value*
Spatial error												
Robust Lagrange multiplier	6.98***	0.008	12.67***	0.000	4.71**	0.030	1.12	0.291	0.05	0.831	0.25	0.618
Spatial lag												
Robust Lagrange multiplier	22.35***	0.000	0.81	0.369	0.50	0.480	0.00	0.961	17.52***	0.000	13.98***	0.000
Number of regions	160		206		160		206		160		206	

* significant at 10%, ** significant at 5%, *** significant at 1%.



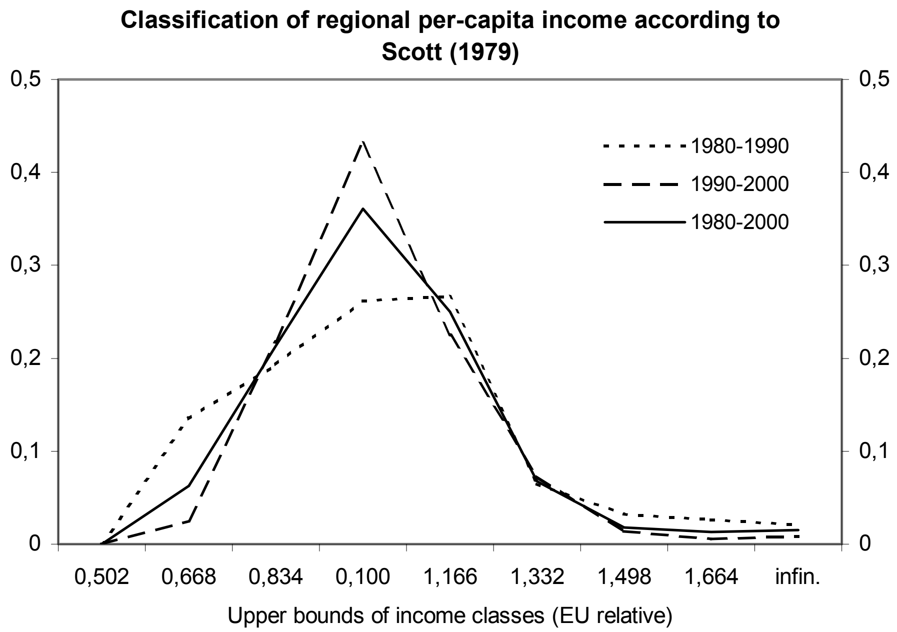


Fig A1. Limiting distributions estimated for different periods of observation