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Regional disparities in the European Union: Convergence and Agglomeration

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Regional Disparities in the European Union: Convergence and Agglomeration

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Preliminary version

Abstract

Economic disparities between the regions of the European Union are of constant concern both for policy and economic research. One of the “stylised facts” from the empirical literature is that the process of absolute convergence observed for decades has slowed down or even petered out during the 1980s. In this paper we analyse whether it has resumed and persisted in the 1990s when European integration made huge steps forward. We construct a typology of regions in order to examine whether there are overlapping trends of regional development, in particular, overall convergence on the one hand and persistent or even increasing spatial concentration (agglomeration) on the other. Both of our approaches, Markov chain analysis and dynamic panel estimation, provide evidence that regional convergence in the EU15 has become stronger in the 1990s. At the same time there appears to exist a tendency towards further agglomeration of high income economic activities.

Keywords: Regional growth, agglomeration, dynamic panel estimation

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1. Introduction

In this paper we seek to draw a picture of aggregate regional disparities and growth in Europe using two different approaches: explorative analysis of the regional income distribution and econometric analysis of regional growth over the period 1980 to 2000. We construct a typology of regions in order to examine whether there are overlapping trends of regional development, in particular, overall convergence on the one hand and persistent or even increasing spatial concentration (agglomeration) on the other. The latter issue is widely unexplored at the European level.

The emergence of new theories of growth and economic geography, political concerns about cohesion in the expanding and further integrating EU and improved data availability have sparked a wave of empirical research on regional development in Europe in the 1990s. A number of stylised facts can be gleaned from the literature:

- (1) The longstanding process of diminishing regional income disparities in Europe slowed down considerably in the 1980s, and it is uncertain whether it has regained momentum since (Barro, Sala-i-Martin 1995; Armstrong 1995; Neven, Gouyette 1995; Tondl 1999; López-Bazo et al. 1999; Boldrin, Canova 2001; Cuadrado-Roura 2001; Martin 2001; Rodriguez-Pose, Fratesi 2002; Villaverde Castro 2002). This appears surprising given the enormous expansion of structural spending during the last two decades.
- (2) There is considerable income convergence at the level of nations. However, regional disparities within the EU member states persist or even grow (Cuadrado-Roura 2001; Martin 2001; Puga 2001; Giannetti 2002; Rodriguez-Pose, Fratesi 2002; Terrasi 2002; European Commission 2003).
- (3) There are spatial effects in the process of regional growth. Neighbouring regions tend to grow at similar speeds (Armstrong 1995; Quah 1996a; López-Bazo et al. 1999; Maurseth 2001; Paci, Pigliaru 2002).¹
- (4) In the 1970s regional disparities in labour productivity (GDP per worker) were much greater than differences in per capita income, but since then convergence

¹ Findings on the question of "convergence clubs" - regions with the same steady state, but not necessarily clustered geographically - are mixed (more in favour: Neven, Gouyette 1995; Canova, Marcet 1995; Tondl 1999; more against: Armstrong 1995; Boldrin, Canova 2001).

of productivity was significantly stronger than that of per capita income (Lopez-Bazo et al. 1999; Esteban 2000; Martin 2001; Basile et al. 2003). The decline of agricultural employment on the one hand and the spatial dispersion of manufacturing on the other are likely to be important factors behind this development (Brülhart, Torstensson 1996; Midelfart-Knarvik et al. 2000; Midelfart-Knarvik, Overman 2002).

- (5) While the core periphery pattern of manufacturing is weakening, service industries appear to be shifting towards the centre of the EU (Brülhart, Traeger 2003).

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). By now it is widely accepted that empirical models that do not account for such effects are misspecified (Fingleton 2003). 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, but due to data availability this concept is difficult to implement in a comprehensive way. Yet another discussion is concerned with estimation techniques (e.g. Badinger et al. 2002). Recently there has been considerable progress in coping with endogeneity and weak instruments in panel econometric analysis of regional growth processes.

In the present study we combine elements of these discussions on the empirical assessment of regional growth in Europe. We first use standard techniques to describe the shape and behaviour over time of the regional income distribution and the mobility of regions within this distribution. Second, we apply dynamic panel estimation to analyse growth of aggregate per capita income of the EU regions over the period from 1980 to 2000. For these estimations a classification of regions was developed ranging from large urban regions to rural areas. Our analyses are motivated mainly by two questions: Has 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

urban areas, levelled off in the course declining communication costs due to the rapid development in the production and application of information and communication technology?

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 argument that regressions miss important information contained in the data on regional growth (Quah 1993, 1996b) we proceed in two stages: first, description of the regional income distribution and its changes, second, panel regressions over the period from 1980 to 2000. In the first stage we estimate density functions for the years 1980, 1990 and 2000. Comparison of these three functions reveals interesting information on the process of regional growth in Europe. The regional distribution of per capita income is then discretised into income classes. The intra-distributional mobility of regions during the periods observed allows the calculation of transition probability matrices that are the basis for the determination of limiting distributions characterising steady-state. GDP per capita in region r at time t is denoted Inc_r^t . If the sequence $\{\text{Inc}_r^0, \text{Inc}_r^1, \dots\}$ satisfies the relation

$$\Pr\{\text{Inc}_r^{t+1} \in i | \text{Inc}_r^t, \text{Inc}_r^{t-1}, \dots, \text{Inc}_r^0\} = \Pr\{\text{Inc}_r^{t+1} \in i | \text{Inc}_r^t\}$$

for any region and class i , then the cross-sectional distribution can be analysed as a time-homogeneous Markov chain (Magrini 1999). The Markov chain itself is described as:

$$\text{Inc}_r^{t+1} = M^n \cdot \text{Inc}_r^t$$

with M^n as the matrix of transition probabilities from one income class to another after n periods. The matrix contains the percentages of regions either remaining at their present level, indicated by the diagonal of the matrix, or shifting up- or downwards in the distribution. From this transition probability matrix a steady state, Inc^* , reached

after n periods, is derived as a distribution where the conditional probability of being in a certain income class is the same as the unconditional probability, i.e.

$$\lim_{n \rightarrow \infty} \text{Inc}_r^t \cdot M^n = \text{Inc}^* .$$

The pace to this steady state can be examined by the second eigenvalue (λ_2) of the transition probability matrix M . If λ_2 is less than 1 convergence exists. Thus, an eigenvalue close to zero indicates a higher convergence rate than a value close to unity. To account for the length of the underlying period of observation Shorrocks (1978) defined a half life (hl) of the system as

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

Multiplying hl by the number of years in the underlying period gives the time the system needs to reach half the distance to its steady state. It ranges between zero (indicating instantaneous convergence) and infinity (no convergence).

The Markov chain approach requires a transition probability matrix which in turn requires regional classification. Arbitrary criteria such as quartiles or percentage deviations from the mean (Quah, 1993, 1996b; Webber, 2001) can be used to subdivide the regional distribution. This discretisation, however, can distort the model and remove the Markov property (Chung, 1960). In order to reduce the arbitrariness Magrini (1999) proposes a procedure to optimise the bin width of cross-sectional classes.

The discretisation approximates the underlying continuous distribution of GDP values. More classes improve the approximation but, at the same time, the probability to derive non-communicating subsets within the matrix increases. The use of fewer classes may only roughly approximate the continuous distribution and substantial information of the cross-sectional dynamics may be lost. An optimisation procedure should therefore try to balance the deficits. Two approaches use the standard deviation and the number of cases to calculate class sizes (Devroye & Györfi, 1985; Scott, 1979). Due to the error terms used in the optimisation procedure different constants enter the formulas:

$$h_n^* = 3.49 \cdot \text{sd} \cdot n^{-\frac{1}{3}} \quad (\text{Scott, 1979}).$$

$$h_n^* = 2.72 \cdot \text{sd} \cdot n^{-\frac{1}{3}} \quad (\text{Devroye \& Györfi, 1985}).$$

In the present case it turns out that the results are extremely sensitive to the choice of classes. Therefore we apply both approaches to document the differences (section 4).

Dynamic panel data analysis of convergence

The typical regression for testing conditional β convergence using panel data is based on the following specification

$$(1) \quad \log y_{it} - \log y_{i,t-1} = b_{0i} - b_1 \log y_{i,t-1} + a_1 x_1 \cdots + a_p x_p + \varepsilon_{it}$$

where b_{0i} denote regional-specific effects, x_1, \dots, x_p are exogenous variables upon which convergence is conditional, ε_{it} denotes an independent and identically $N(0, \sigma^2)$ distributed error, and $b_1 = 1 - \exp(-\beta)$. In case of conditional convergence we expect $b_1 > 0$ and in turn $\beta > 0$. In many cases (1) is estimated using OLS (LSDV estimation).

Note that (1) can be written as

$$(2) \quad \log y_{it} = b_{0i} - (b_1 + 1) \log y_{i,t-1} + a_1 x_1 \cdots + a_p x_p + \varepsilon_{it}.$$

Apparently, this is a dynamic panel data model which – due to the inclusion of a lagged dependent variable – will render OLS estimation of b_1 inconsistent and biased. Consistent estimates, however, can be obtained by a GMM type estimator as has been proposed by Arrelano and Bond. As proposed by Bond, Hoeffler and Temple (2001), we use an extended version of this estimator (system GMM) which is outlined in Arellano and Bover (1995) and fully developed in Blundell and Bond (1998).

First-differencing of equation (2) removes the b_{0i} , thus eliminating a potential source of omitted variable bias in estimation. However, in first differences, the predetermined variable $\log y_{i,t-1}$ become endogenous. Arellano and Bond (1991) developed a Generalized Method of Moments estimator that treats the model as a system of equations, one for each time period. The equations differ only in their instrument/moment condition sets. The predetermined and endogenous variables in first differences are instrumented with suitable lags of their own levels. Strictly exogenous

regressors, as well as any other instruments, can enter the instrument matrix in the conventional instrumental variables fashion: in first differences, with one column per instrument.

A problem with the original Arellano-Bond estimator is that lagged levels are often poor instruments for first differences, especially for variables that are close to a random walk. Arellano and Bover (1995) described how, if the original equations in levels were added to the system, additional moment conditions could be brought to bear to increase efficiency. In these equations, predetermined and endogenous variables in levels are instrumented with suitable lags of their own first differences. Blundell and Bond (1998) articulate the necessary assumptions for this augmented estimator more precisely and tested it with Monte Carlo simulations. The original estimator is sometimes called "difference GMM", and the augmented one, "system GMM".²

As Bond, Hoeffler and Temple (2001) point out, in the case of dynamic panel data growth regression the problem of weak instruments is likely to be present, since the income series is highly persistent. Therefore, these authors argue in favour of the more efficient system GMM, which in their empirical analysis turns out to give more reasonable results in the growth regressions than the first-differenced GMM.

Our dependent variable is defined as difference between log of regional income and log of weighted EU15 income average. Note that there is a difference between the weighted E15 income average and the sample mean of income of all regions. Due to this difference is still possible to add time dummies to the regressions (which would otherwise have cancelled out). Though the significance of the year effects is reduced by this definition, the remaining year effects will capture the difference between weighted EU15 income mean and average income of all regions.

The conditioning X variables in the growth regressions are (1) country effects and (2) type of region.³ Neither the investment rate nor human capital endowment could be included as in Bond, Hoeffler and Temple (2001) since this data is not available at the regional EU level. Nevertheless, we argue that despite these potentially omitted variables our estimations appear to be quite reasonable. Firstly, these series usually do not possess much within variation, so that that their effects are removed as part of

² Bond (2002) is a good introduction to these estimators and their use.

unobserved heterogeneity when taking first differences. Second, because of mobility of human capital within a country it more reasonable to include such measures at the country level.

In order to capture country-specific effects e.g.

- national networks (neighbourhood effects)
- national institutions e.g. education, infrastructures and policies
- country-specific preferences, cultures and behaviours
- country-specific differences in EU structural policies

we added country effects to the first differences equations. The first effect of the inclusion of country effects is worth stressing, since as Fingleton (2003) shows, the inclusion of country dummy variables might reduce the amount of regional spatial correlation considerably.

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 (one prominent exception is Cheshire and Carbonaro 1996). However, the resulting set of units of observation is 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 delimitation of functionally integrated units of observation.⁴ For lack of comprehensive information on commuting patterns the

³ Note that the dummy variables corresponding to these effects are added to equation (2) in first differences. If they were added to the equation in level they would cancel out when taking first differences.

⁴ 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.

combination of statistical units to functionally integrated areas 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.

Corresponding to our aim to analyse simultaneously patterns of regional growth and spatial concentration we have to construct a system of regions ranked according to the degree of urbanisation. We choose 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 300 inhabitants per square kilometre. Typically, these regions include one or two smaller cities 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 300 inhabitants per square kilometre. The number of regions assigned to each group is shown in Table A1 in the Appendix.

As a consequence of our choice of regions the empirical analysis is restricted to the rather limited set of data available at the NUTS3 level. We use population and income data from EUROSTAT REGIO database. We 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 1995-1999) 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 in the NUTS3 data in 1991 and 1993, respectively.

Because of these gaps in the time series of GDP and population data we have to construct two data sets, one for each of stage of our empirical analysis. For the analysis of the regional distribution of per capita incomes we need a balanced panel with data for all regions for the years 1980, 1990 and 2000. Here, countries with incomplete time series of regional data enter with their national values for all three years. This applies to five small countries of the EU. Similarly, Northern Ireland and Scotland are each taken

as a whole. East Germany has to be left out completely. Eventually, we end up with data for 168 regions covering all of the EU15 except the eastern part of Germany.⁵

In the econometric analysis we can do with an unbalanced panel. Here, our regional concept can be applied without restrictions. Regions are included as data become available. Altogether, we have 207 regions and almost 80% of them are represented in the data from the beginning of the period observed (see Table A2 in the Appendix).

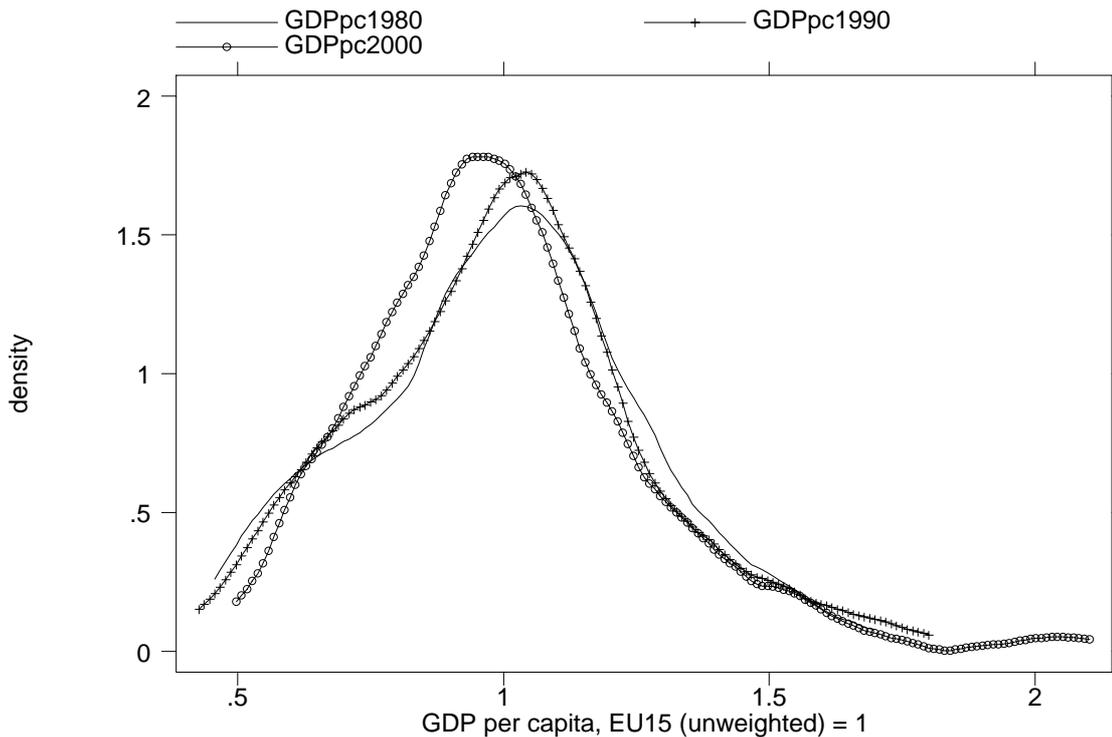
4. Results

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 disappeared. Obviously, European regions are not developing towards a twin-peak situation diagnosed by Quah (1996b) for the world economy. 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 was 2.1 (Luxemburg) in 2000 compared to 1.8 (Munich) in 1990 and 1.7 (Paris) in 1980. In 2000 the income of 7 regions exceeded the EU average by more than 50% compared to 4 regions in 1980. 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.

Figure 1 Regional distributions of per capita income

⁵ The region Groningen was dropped from this data set. Groningen is the centre of the Dutch gas industry and exhibited extreme changes of per capita income in the 1980s, mainly due to fluctuations of gas prices.



Altogether, we observe changes in the regional distribution of income both towards polarisation and equalisation, but the latter force appears to dominate. This issue will be further discussed in connection with the analysis of the mobility of regions between discrete income classes.

The two ways of discretising the regional distribution of per capita income described in section 2 produce different class sizes as can be seen in Table 1. Scott's method yields nine classes with a bin width of about 0.167, i.e., each class comprises 16.7 percentage points of the regional distribution of EU relative income (unweighted EU15 average = 1.000). The income classes according to Scott are shown in Table A3 in the Appendix. The class sizes resulting from Devroye and Györfi's method (DG) are somewhat smaller, about 13 percentage points.

Table 1 Class sizes for different periods and methods

Time period	Method	Class size
1980-1990	Scott	0.167
1990-2000		0.169
1980-2000		0.166
1980-1990	Devroye/Györfi	0.130
1990-2000		0.132
1980-2000		0.130

The results derived from the Marcov process with respect to the existence and the speed of regional convergence are very sensitive to class size. As can be seen in Table 2 the second eigenvalues and the associated half life values vary substantially depending on the method used. The ‘pace towards steady state’ measured by the Scott approach are far lower than the DG results, at least for the whole period and the first sub-period. Extremely high eigenvalues, as with DG, are caused by absorbing classes in the transition probability matrix. An absorbing class is one that a region never leaves once it has entered it. Eventually, all regions will approach that class, but this process is very long slow.

For the 1990s Scott’s method, too, produces an extremely high half life value. But again, this result is highly sensitive to the classification. From 1990 to 2000 the EU relative per capita income of Paris (Ile de France) fell from 1.77 to 1.69. The region remained in the highest income class but ended up very close to the lower border of the class (1.667). A minimal manipulation of the data would shift Paris downward and this, in turn, would change results entirely (see Table 2, Scott (Paris changed)). This manipulation removes the absorbing property in the transition matrix and leads to an indication for a higher speed in approaching the steady state in the 1990s compared to the 1980s. The half life time drops from 91 years to 71 years.

Table 2 Second eigenvalues and pace towards steady state for different periods and methods

Time period	Method	Second eigenvalue	Half life*years in the basic period observed
			(pace towards steady state)
1980-1990	Scott	0.919	90.8
1990-2000		0.998	3944.7
1980-2000		0.859	95.7
1980-1990	Scott (Paris changed)	0.919	90.8
1990-2000		0.899	71.3
1980-2000		0.836	81.4
1980-1990	Devroye/Györfi	0.998	3299.7
1990-2000		0.999	8274.8
1980-2000		1.000	∞

The steady-state distribution estimated from the regional mobility during the period from 1980 to 2000 is shown in the bottom row of Table A3 in the Appendix. It is much tighter than the initial distribution for 1980 and also tighter than the one for 2000. In the limit the two lowest and the two highest income classes are virtually empty. This result together with the related half life time of 96 years indicates a process of slow convergence, but as shown above this cannot be taken as a robust finding. At least with our sample and period of observation first-order time-homogeneous Markov chain analysis does not lead to reliable estimates of the speed of convergence. In particular, the question whether there has been an acceleration of convergence in the second half of the period, the 1990s, cannot be answered.

Nevertheless, the transition probability matrix for the period from 1980 to 2000, calculated according to Scott (see section 2), reveals interesting information. The changes in the shape of the regional distribution of per capita income (Figure 1) are not the result of volatile movements. In 2000 more than half of the regions were in the same income class as in 1980.⁶ Most regions that have changed their position moved just one class up or down and hardly any region jumped across more than two classes. All regions but one with initial income below 83% of the (unweighted) EU average have kept or improved their position since, i.e. if anything, relatively poor regions become richer, not poorer. Matrices for the two sub-periods (not reported here) show that this process was significantly stronger in the 1990s than in the 1980s.⁷ Real churning of the distribution is happening in the middle. Many regions with above average or just below average incomes in 1980 fell back in the ranking until 2000. Finally, the top of the income hierarchy is formed by a small and persistent group of urban regions. The 4 leaders in 1980 (Paris, Brussels, Munich and Stuttgart) were still at the top (more than 50% above average) in 2000, now together with Luxemburg, Frankfurt and Utrecht.⁸

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 gradually decreasing; this tendency was hardly existing in the 1980s, but stronger in the 1990s. Convergence occurred through catching-up of the poorest regions

⁶ Of course, there have been transitions in the meantime, but generally these too were smooth rather than abrupt.

⁷ To check for intra-class effects we calculated a transition probability matrix according to Devroye/Györfi with smaller and therefore more income classes (11 instead of 9). The results for the poorest regions are the same.

⁸ A similar result is found by Magrini (1999) and Cheshire, Magrini (2000) for the period 1978-1994, though their group of leading urban regions is somewhat different from ours. GDP for Luxemburg may be exaggerated due to problems of measurement and regional assignment of output for the finance sector.

and relatively weak growth of many regions with initially above average income. Second, a small group⁹ of large urban regions retains its position at the top of the income hierarchy. This might be an indication for a broader tendency towards agglomeration of (certain) economic activities.

Growth regressions

Our basic results without including conditioning variables are reported in Table A4. The first three columns report the results using OLS levels, Within Groups, first-differenced GMM and system GMM estimators respectively. Note that because the number of time periods is rather high, we report two-step estimates instead of one-step estimates except for sub-period estimations, where one-step estimates are reported.

As in Bond, Hoeffler, Temple (2001) the first-difference GMM estimate of the coefficient of lagged income (col. 3) is likely to be seriously biased, because it is below the Within-group (WG) estimate. The system GMM estimator, on the other hand, is – as expected – lower than the OLS level estimate (but only slightly below). Taking both the increased precision and the reasonable magnitude of the estimate into account, it can be argued that also in our case system GMM is a considerable improvement compared to first-differenced GMM.

The results with included conditioning variables are displayed in Table A5. Estimation results where sub-periods 1980-1989 and 1990-2000 are compared are presented in Table A6.

The main findings of the growth regressions can be summarized as follows:

- (1) As the results of the system GMM estimation in Table A4 indicate, the estimate for the lagged income variable implies a convergence rate b_1 of 2.4 percent. The 95% confidence interval for this convergence rate is [1.5, 5.3].¹⁰ Thus, our results are quite comparable to those reported in Bond, Hoeffler, Temple (2001), even if their growth regression are performed at the country and not at the regional level and included additional conditional variables.

⁹ Since OLS (level) is upward and Within-Group estimation is downward biased, we expect that a reasonable estimate would be within the range of OLS (level) and Within-Group estimate (see Bond, Hoeffler, Temple 2003).

¹⁰ Note that for such small values of b_1 (sufficiently close to zero), the difference to β is negligible.

- (2) Including country effects (Table A5, col. 1) leads to a somewhat higher estimated convergence rate of 3.5 (in percent) with a 95% confidence interval [2.1, 4.9]. Note that the (excluded) reference country is Austria.
- (3) Results for the type of region dummy variables indicate (Table A4., col.2) that agglomerated regions have a 1 percent higher expected growth rate of income than rural regions. The calculated convergence rate is 4.1 with a 95% confidence interval (in percent) of [2.6, 5.7].
- (4) The results were checked regarding their the robustness with respect to extreme low or high growth rates (reversion to the mean phenomenon). Col. 3 of Table A5 contains the results for regions within the 5-95% sample range of growth rates, and col. 4 the results for regions within the 25-75% range. For the first sub-sample, the implied rate of convergence is indeed considerably lower compared to the full sample with a value of about 1 percent, and a 95% confidence interval of [0.2, 1.8]. For the within 25-75 % sample range of growth rates we find a convergence rate of about 0.9 and a 95% confidence interval of [-0.7, 2.4]. Thus, for this case the convergence rate is not statistically significant different from zero at least at the five percent level.
- (5) Comparing the two sub-periods 1980-1989 and 1990-2000 (Table A5), the mean rate of convergence for the first period is 2.6 with a 95% confidence interval of [1.0 ,4.1]. The estimated convergence rate for the period 1990-2000 is considerably higher with a value of 5.4. However, the corresponding 95 % confidence interval is [3.3, 7.5], which shows that the estimation for the second period is relatively imprecise. Since both confidence intervals overlap, the estimate of 5.4 is not statistically different from 2.6 at a 5 percent level.

To summarize, the estimations provide evidence of a convergence rate in the range of 2 to 4 percent, depending on the specification. This is considerable lower than in many other studies, except Bond, Hoeffler and Temple (2001). We furthermore find that the estimate of the average convergence rate in the 1990s is higher than that for the 1980s, albeit the difference is statistically not significant. Agglomerated regions have a 1 percent higher growth rate than rural regions. Finally, the results for convergence rates are relatively robust when the upper and lower part of the income growth distribution of regions is disregarded.

5. Conclusions

Disparities in per capita income between the regions of the EU15 are gradually decreasing. This might be a result of inherent convergence forces as predicted by neoclassical growth theory or a result of income re-distribution within the EU. Our results support the view that the process of convergence was hardly present in the 1980s, but stronger in the 1990s. Convergence occurred both through catching-up of the poorest regions and relatively weak growth of many (erstwhile) richer regions. At the same time there appears to exist a tendency towards further agglomeration of high income economic activities. The co-existence of these two forces may, at least partly, explain why many empirical analyses find evidence for convergence among European countries but not among regions within countries.

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Appendix

Table A1: Number of observed regions by type

Type	Number of regions
Large urban areas	42
Small urban areas	36
Intermediate regions	33
Rural regions	96
Total	207

Table A2: Number of observed regions by length of time series

Period covered by data	Number of regions
1980-2000	161
1985-2000	6
1988-2000	15
1991-2000	13
1993-2000	7
1994-2000	4
1995-2000	1
Total	207

Table A3: Mobility of regions between income classes from 1980 to 2000 (transition probabilities in brackets).

EU (unweighted) = 1.000	Year 2000								
	< 0.499	0.499 - 0.666	0.666 - 0.833	0.833 - 1.000	1.000 - 1.167	1.167 - 1.334	1.334 - 1.501	1.501 - 1.667	> 1.667
Year 1980	< 0.499	1 (0.250)	2 (0.500)	1 (0.250)	0	0	0	0	0
	0.499 - 0.666	0	7 (0.389)	8 (0.444)	2 (0.111)	0	1 (0.056)	0	0
	0.666 - 0.833	0	1 (0.048)	15 (0.714)	5 (0.238)	0	0	0	0
	0.833 - 1.000	0	0	5 (0.143)	21 (0.600)	8 (0.228)	1 (0.029)	0	0
	1.000 - 1.167	0	0	0	19 (0.422)	23 (0.511)	3 (0.067)	0	0
	1.167 - 1.334	0	0	0	5 (0.192)	8 (0.308)	11 (0.424)	0	1 (0.038)
	1.334 - 1.501	0	0	0	0	0	4 (0.333)	7 (0.584)	1 (0.083)
	1.501 - 1.667	0	0	0	0	0	0	2 (0.500)	1 (0.250)
	> 1.667	0	0	0	0	0	0	0	1 (0.500)
	Distribution in 1980	0.024	0.108	0.126	0.210	0.269	0.156	0.072	0.024
Distribution in 2000	0,006	0,060	0,174	0,311	0,234	0,120	0,054	0,024	0,018
Stationary distribution	0.000	0.017	0.210	0.369	0.205	0.051	0.012	0.010	0.004

Table A4: Dynamic Panel Data Estimation Results

	Period 1981-2000		Period 1981-2000		Period 1982-2000		Period 1982-2000	
	<i>OLS level</i>		<i>Within</i>		<i>GMM-Dif</i>		<i>GMM-Sys</i>	
	Coefficient	Std.Error	Coefficient	Std.Error	Coefficient	Std.Error	Coefficient	Std.Error
Constant	-0.0023	0.00234	-	-	-	-	-0.0027	0.00236
logY(-1)	0.9786	0.00396	0.8041	0.02137	0.7243	0.04222	0.9764	0.00432
1982	-0.0002	0.00291	-0.0002	0.00265	-0.0002	0.00252	0.0011	0.00317
1983	-0.0028	0.00323	-0.0028	0.00294	-0.0021	0.00451	-0.0043	0.00362
1984	-0.0004	0.00328	-0.0009	0.00304	0.0016	0.00383	-0.0027	0.00382
1985	0.0016	0.00394	0.0011	0.00372	0.0025	0.00455	0.0024	0.00511
1986	-0.0076	0.00443	-0.0068	0.00434	-0.0072	0.00588	-0.0097	0.00521
1987	-0.0030	0.00369	-0.0036	0.00380	0.0019	0.00388	-0.0020	0.00370
1988	0.0093	0.00484	0.0082	0.00459	0.0120	0.00435	0.0146	0.00648
1989	0.0023	0.00276	0.0026	0.00304	-0.0033	0.00454	0.0028	0.00303
1990	-0.0059	0.00316	-0.0053	0.00324	-0.0075	0.00362	-0.0086	0.00342
1991	0.0055	0.00322	0.0051	0.00331	0.0104	0.00374	0.0085	0.00340
1992	0.0103	0.00407	0.0041	0.00321	-0.0033	0.00333	0.0084	0.00388
1993	0.0123	0.00387	0.0080	0.00363	0.0047	0.00318	0.0180	0.00454
1994	0.0040	0.00283	0.0022	0.00303	-0.0041	0.00365	0.0056	0.00317
1995	0.0034	0.00359	0.0018	0.00373	-0.0003	0.00336	0.0032	0.00430
1996	-0.0006	0.00303	-0.0015	0.00356	-0.0028	0.00347	-0.0001	0.00309
1997	0.0013	0.00279	0.0003	0.00350	0.0018	0.00343	0.0018	0.00285
1998	-0.0043	0.00250	-0.0051	0.00316	-0.0050	0.00335	-0.0063	0.00257
1999	0.0016	0.00277	0.0001	0.00342	0.0049	0.00318	0.0014	0.00280
2000	-0.0038	0.00263	-0.0051	0.00318	-0.0044	0.00290	-0.0069	0.00282
observations	3685		3685		3478		3685	
regions	207		207		207		207	
longest time	20		20		19		20	
shortest time	5		5		4		5	
No. of param	21		227		20		21	
sigma	0.033		0.030		0.037		0.0334	
RSS	4.061		3.184		4.812		4.083	
TSS	269.277	p-value	12.472	p-value	3.680	p-value	269.277	p-value
AR(1)	3.459	0.001	3.359	0.001	-6.092	0.000	-6.706	0.000
AR(2)	0.304	0.761	-0.438	0.661	-1.56	0.119	-1.558	0.119
Sargan	-	-	-	-	197.4	0.074	203	0.247

Note: Heteroscedaticity robust standard errors are reported.

Table A5: Dynamic Panel Data GMM-Sys Estimation Results

	Period 1981-2000		Period 1981-2000		Period 1982-2000		Period 1982-2000	
	<i>GMM-Sys</i>		<i>GMM-Sys</i>		5-95 % range <i>GMM-Sys</i>		25-75 % range <i>GMM-Sys</i>	
	Coefficient	Std.Error	Coefficient	Std.Error	Coefficient	Std.Error	Coefficient	Std.Error
Constant	0.00305	0.00390	0.00301	0.00418	0.00615	0.00265	0.00746	0.00488
logY(-1)	0.96490	0.00705	0.95880	0.00795	0.99011	0.00406	0.99124	0.00789
Reg type 1	-	-	0.00969	0.00305	0.00406	0.00173	0.00332	0.00294
Reg type 2	-	-	0.00468	0.00245	0.00247	0.00160	0.00226	0.00263
Reg type 3	-	-	0.00055	0.00320	-0.00028	0.00190	-0.00220	0.00239
1982	0.00082	0.00320	0.00092	0.00312	-	-	-	-
1983	-0.00422	0.00359	-0.00411	0.00355	-0.00527	0.00296	-0.00900	0.00348
1984	-0.00258	0.00383	-0.00230	0.00381	-0.00025	0.00308	0.00362	0.00460
1985	0.00259	0.00505	0.00231	0.00496	-0.00005	0.00368	0.00553	0.00404
1986	-0.00900	0.00521	-0.00892	0.00518	0.00318	0.00411	-0.00291	0.00532
1987	-0.00192	0.00377	-0.00167	0.00369	-0.00914	0.00455	-0.00471	0.00457
1988	0.01461	0.00637	0.01463	0.00622	0.00160	0.00309	-0.00089	0.00486
1989	0.00266	0.00305	0.00284	0.00302	0.00811	0.00777	0.00263	0.00640
1990	-0.00838	0.00342	-0.00802	0.00338	-0.00277	0.00344	0.01285	0.00697
1991	0.00844	0.00336	0.00842	0.00334	0.00362	0.00333	0.00613	0.00414
1992	0.00679	0.00360	0.00688	0.00351	-0.00139	0.00355	0.00615	0.00551
1993	0.01621	0.00424	0.01600	0.00416	-0.00091	0.00322	0.00156	0.00739
1994	0.00438	0.00301	0.00445	0.00303	-0.00015	0.00339	-0.00284	0.00585
1995	0.00233	0.00434	0.00236	0.00423	0.00053	0.00279	-0.00478	0.00522
1996	-0.00097	0.00314	-0.00097	0.00310	-0.00160	0.00328	-0.00200	0.00698
1997	0.00102	0.00291	0.00089	0.00289	-0.00009	0.00267	-0.00991	0.00497
1998	-0.00683	0.00270	-0.00667	0.00269	-0.00368	0.00252	-0.00425	0.00505
1999	0.00046	0.00284	0.00047	0.00282	0.00060	0.00261	-0.00123	0.00351
2000	-0.00745	0.00291	-0.00740	0.00287	-0.00728	0.00254	-0.00054	0.00352
BE	-0.00749	0.00444	-0.01169	0.00486	-0.00896	0.00264	-0.00910	0.00482
DE	0.00038	0.00356	-0.00235	0.00430	-0.00804	0.00244	-0.00711	0.00459
DK	0.00618	0.00341	0.00215	0.00416	0.00305	0.00316	0.00965	0.00546
ES	-0.00980	0.00383	-0.01553	0.00462	-0.00336	0.00246	0.00267	0.00486
FI	-0.00661	0.00767	-0.00782	0.00748	-0.01456	0.00713	-0.01538	0.01481
FR	-0.01266	0.00320	-0.01458	0.00360	-0.01449	0.00191	-0.02302	0.00462
GR	-0.01921	0.00506	-0.02370	0.00558	-0.00705	0.00406	-0.00386	0.00874
IE	0.03762	0.00724	0.03333	0.00748	0.08213	0.02012		
IT	-0.00493	0.00362	-0.00892	0.00434	-0.00656	0.00225	-0.00853	0.00437
LU	0.03882	0.01671	0.03573	0.02078	0.03846	0.01118	0.11665	0.04597
NL	-0.00369	0.00420	-0.00762	0.00495	-0.00819	0.00492	-0.00876	0.00742
PT	-0.01526	0.00622	-0.02167	0.00638	0.00102	0.00344	0.03038	0.01086
SE	-0.01422	0.00454	-0.01561	0.00401	-0.01801	0.00255	-0.03430	0.00857
UK	-0.00815	0.00311	-0.01298	0.00393	-0.00825	0.00243	-0.01050	0.00503
observations	3685		3685		3110		1624	
regions	207		207		207		192	

longest time	20		20		18		18	
shortest time	5		5		1		1	
No.of param.	35		38		37		36	
sigma	0.033		0.033		0.032		0.037	
RSS	3.909		3.873		3.071		2.229	
TSS	269.277	p-value	269.277	p-value	204.753	p-value	95.039	p-value
AR(1)	-6.711	0.000	-6.701	0.000	-4.157	0.000	-3.747	0.000
AR(2)	-1.548	0.122	-1.549	0.121	0.6136	0.539	0.7104	0.477
Sargan	199.4	0.306	196.8	0.353	197.8	0.078	140.6	0.957

Note: Heteroscedaticity robust standard errors are reported.

Table A6: Dynamic Panel Data GMM-Sys Estimation Results for sub-periods

	Period 1980 - 1989		Period 1990 - 2000	
	GMM-Sys		GMM-Sys	
	Coefficient	Std.Error	Coefficient	Std.Error
Constant	-0.00622626	0.003508	0.00850431	0.003376
logY(-1)	0.974064	0.007889	0.946041	0.01054
Reg type 1	0.00561528	0.002741	0.0124363	0.003636
Reg type 2	0.00409544	0.002348	0.0063482	0.002803
Reg type 3	0.00018636	0.002241	0.00164214	0.003294
1982	0.00071115	0.003146	-	-
1983	-0.0047887	0.003591	-	-
1984	-0.00317494	0.00385	-	-
1985	0.00219314	0.005105	-	-
1986	-0.00994168	0.00523	-	-
1987	-0.00200143	0.00369	-	-
1988	0.0141675	0.006234	-	-
1989	0.00200965	0.002947	-	-
1992	-	-	0.00167744	0.00351
1993	-	-	0.0106101	0.004242
1994	-	-	-0.00150429	0.003339
1995	-	-	-0.00368885	0.004063
1996	-	-	-0.00713289	0.002927
1997	-	-	-0.00484867	0.003227
1998	-	-	-0.0129061	0.003035
1999	-	-	-0.00487243	0.002437
2000	-	-	-0.0138064	0.003075
BE	-	-	-0.0130624	0.004994
DE	0.00568588	0.002918	-0.00462826	0.003539
DK	-	-	0.00761454	0.002908
ES	0.0006963	0.003873	-0.020319	0.005098
FI	-	-	-0.00804445	0.00859
FR	-0.00079627	0.002895	-0.0187537	0.00299
GR	-0.00891901	0.005609	-0.0225156	0.006893
IE	-	-	0.0330026	0.007514
IT	0.00226286	0.002935	-0.0108699	0.004261

LU	0.0419484	0.004352	0.0462449	0.005808
NL	-0.00450844	0.005081	-0.00232173	0.004507
PT	-0.00316499	0.00581	-0.0227746	0.007057
SE	-0.0011375	0.003874	-0.0174095	0.003674
UK	0.0059282	0.002989	-0.0173149	0.00385
observations	1473		2015	
regions	167		207	
longest time	8		9	
shortest time	3		4	
no.of param	23		28	
sigma	0.036		0.030	
RSS	1.856		1.825	
TSS	119.338		135.075	
AR(1)	-4.412	0.000	-8.169	0.000
AR(2)	-1.676	0.094	1.310	0.190
Sargan	390.2	0.000	820.100	0.000

Note: Heteroscedaticity robust standard errors are reported.