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Agglomeration, Spatial Interaction and Convergence in the EU

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Abstract

We investigate the convergence process among EU regions between 1980 – 2002 taking into account the effects of spatial heterogeneity and spatial spillover effects. The spatial regimes model allows for different steady-state growth paths. In contrast to previous analyses, the regimes in this paper refer to spatial categories, i.e. we assume that agglomerations, urbanised and rural regions are characterised by group-specific steady-states. Moreover, the regression analysis considers the effects of interaction among neighbouring regions, possibly leading to a spatial dependence of regional growth rates. We check whether spatial dependence is caused by spatial spillovers or is based on country effects.

Zusammenfassung

Das Papier untersucht den Konvergenzprozess für EU Regionen zwischen 1980 – 2002. Dabei wird der räumlichen Heterogenität und räumlichen Interaktionen explizit Rechnung getragen. In verschiedenen Regionstypen sind unterschiedliche Steady-State-Wachstumspfade möglich. Im Gegensatz zur bisherigen Literatur findet eine Gruppierung entsprechend räumlicher Kategorien statt. Konkret werden für Agglomerationen, für städtische Regionen und für ländliche Regionen verschiedene gruppenspezifische Wachstumseffekte geschätzt. Darüber hinaus werden Interaktionen zwischen benachbarten Regionen, die zu räumlichen Abhängigkeiten im Wachstumsprozess führen, berücksichtigt. Es wird untersucht, inwieweit räumliche Abhängigkeiten durch räumliche Spillovers entstehen oder auf Ländereffekten basieren.

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1. Introduction

Regional growth and convergence are issues of intense research since the early 1990s initiated at least partly by the development of New Growth Theory and New Economic Geography (NEG). Both theories have important implications regarding the determinants of regional growth and the evolution of regional disparities. Although considerable progress has been made with respect to the knowledge on these issues still new aspects emerge. Recent developments refer to theoretical as well as empirical research. Firstly, as regards advances in theoretical research there are new approaches that incorporate endogenous growth in an NEG framework. Corresponding analyses allow for interesting insights on the relationship between agglomeration and growth. Studies by Martin / Ottaviano (2001) as well as Baldwin / Forslid (2000) establish links between agglomeration, the evolution of regional income differences and the level of overall growth.

Secondly, current empirical work emphasises the spatial dimension of growth and convergence. The new theories stress the significance of spillover effects and there is growing awareness that space matters for growth. Spatial effects are increasingly recognised as an important feature of regional growth processes with a basis in economic theory. Spatial econometric methods enable us to analyse the implication of new theoretical approaches in this respect. Studies by Anselin et al. (1997); Bottazzi / Peri (2003), and Funke / Niebuhr (2005) among others aim at investigating the impact of spatial spillover effects on innovation, growth and regional disparities. Fingleton (2003) argues that spillovers might give rise to spatial dependence of regional growth which has to be dealt with by spatial regression models. Another strand of literature considers spatial heterogeneity in connection with regional convergence. Quah (1996) investigates whether income growth of EU regions is characterised by the formation of convergence clubs. Moreover, analyses by Baumont et al. (2003) and Fischer / Stirböck (2004) indicate that convergence clubs exhibit specific spatial patterns. They detect different spatial regimes in Europe that are characterised generally speaking by a division between Northwest and Southeast. Finally, Crozet / Koenig (2004) investigate whether regional growth in the EU is marked by a tradeoff between growth and cohesion. An implication of recent models which integrate endogenous growth and NEG is that agglomeration, i.e. increasing regional disparities, can be a source of higher growth at the national level.

However, empirical evidence on the various linkages between agglomeration, spillovers and growth is still scarce. This paper aims at providing additional empirical findings on the relevance of these interrelated phenomena. The analysis considers some of the above mentioned issues. We analyse convergence among European regions between 1980 and 2002. More precisely, the paper deals with the question whether convergence clubs, i.e. different spatial regimes mark the development regional income disparities in Europe. The novelty of our study is that, in contrast to the above mentioned studies, it defines spatial regimes starting from a classification of spatial categories. As a basic idea, agglomerations and rural peripheral regions are marked by different steady state equilibria and therefore constitute convergence clubs. We depart from new theoretical models which focus on the link between agglomeration, growth and convergence. This theoretical framework suggests considering both convergence clubs and spatial dependence as potential features of regional growth in Europe.

Moreover, we focus on two statistical issues. As Temple (1999) notes there are many cross-section growth regressions which suffer from serious outliers. Outlying regions can have a marked effect on OLS regression results and therefore more robust estimation methods might be appropriate. In addition, Durlauf (2001) suggest that modelling parameter heterogeneity is one of the crucial topics on the agenda for empirical growth modelling. To address these issues we apply quantile regressions as introduced by Koenker / Basset (1978). Parameter heterogeneity across the conditional distribution has been analysed by Barreto / Hughes (2004) at the country level. To our knowledge, quantile regressions have so far not been used for European regional data.

The rest of the paper is organised as follows. In section 2, we briefly outline the theoretical background of our empirical investigation. The main features and implications of recent theoretical models which exhibit multiple equilibria and integrate NEG and endogenous growth are summarised. The empirical methodology is introduced in section 3. Data and cross section are described in section 4. In section 5, the regression results are presented. We conclude with a summary of the main results in section 6.

2. Theory

Martin / Ottaviano (2001) note that the relationship between growth and agglomeration is already apparent in the changes which mark the industrial revolution in Europe. The sharp increase in economic growth at that time was accompanied by urbanisation, the formation of industrial clusters and increasing regional disparities. According to this observation geography might matter for growth. Fujita / Thisse (2002) argue that agglomeration can be considered as the territorial counterpart of growth. Moreover, the role of cities in economic growth is emphasised. Cities might act as locations where technological and social innovations are developed and, therefore, could be considered as engines of growth. Recently theoretical models have been developed which allow analysing how growth and location impact on each other.

In theoretical approaches that include endogenous growth in an NEG framework, growth and agglomeration of economic activities are mutually self-reinforcing processes: growth brings about agglomeration and agglomeration fosters growth (see Martin / Ottaviano 2001). Models by Fujita / Thisse (2002) as well as Baldwin / Forslid (2000) combine the Krugman core-periphery model with Romer-type endogenous growth. As a main result of corresponding approaches, growth is affected by the spatial distribution of mobile skilled workers who develop new goods in an R&D sector. More precisely, the overall growth rate of the economy depends on the distribution of R&D activity across space. Knowledge capital affecting the productivity of researchers positively is assumed to increase in each region with the interaction of all skilled workers. The interaction among researchers in turn is influenced by the spatial distribution of researchers. Proximity due to agglomeration fosters interaction and innovation.

In general, the analyses differentiate between global and local knowledge spillovers. In case of global spillover effects, i.e. patents for new goods and technological knowledge are transferred costlessly among all regions, the R&D sector is located in a single region since agglomeration forces are strong. Moreover, the industrial sector might be partly or fully agglomerated in the same region. In the model by Ottaviano / Martin (1999), geography will not affect growth, if spillovers are global. Determinants of growth such as the R&D cost impact on regional income differentials and therefore on the location of firms. In this framework, high growth is associated with convergence since factors which increase the growth rate also decrease income differences.

If localised knowledge spillovers are assumed, e.g. because of important tacit knowledge, R&D and industry tend to be entirely agglomerated in one region. R&D activities will move to agglomerated regions, because with local spillovers R&D costs are lowest in agglomerations where firms that produce differentiated products concentrate. Altogether, the R&D sector represents a strong centripetal force which amplifies the cumulative causation. Under specific assumptions the models imply that agglomeration fosters innovation and growth. Agglomeration of skilled workers enables them to generate higher growth and a higher rate of innovation. As in NEG models, agglomeration is associated with increasing disparities in regional per capita income. Growth increases with the degree of industrial agglomeration and hence diverging regional per capita income. Inequality can be a source of more growth, when technological externalities are localised, as Crozet / Koenig (2004) put it. Thus the results suggest a trade off between equity and growth. Both core and periphery enjoy higher growth, but the income gap between centre and periphery increases.[1] To a large extent, regional income disparities reflect the geographical distribution of skills and differences between agglomerations and rural peripheral regions.

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1 However, from a welfare point of view the periphery might still be better off in the agglomeration case, even without transfers, provided the growth effect of agglomeration is strong enough.

However, there is another class of models which predict the existence of convergence clubs. Club convergence can also be derived from growth models, such as in Azariadis / Drazen (1990), which exhibit multiple steady state equilibria. In these kind of models, the steady state equilibrium of a region is determined by its initial conditions, and regions will converge to the same steady state, if they are characterised by similar conditions. Several approaches refer to human capital formation as a cause of club convergence.[2] Due to social increasing returns to scale from human capital accumulation, countries or regions differing with respect to their initial level of human capital might converge to different steady state equilibria. According to Canova (2004), several factors such as the endowment of important factors of production (human capital, public infrastructure, R&D activity), preferences or government policies may induce convergence clubs. As there are systematic differences between agglomerations and rural peripheral regions with respect to human capital endowment, infrastructure and R&D activity, these models reinforce theoretical arguments regarding convergence clubs which correspond with spatial categories. However, the models also provide arguments for an influence of national factors such as national policies or legislation.

With respect to an empirical analysis of regional growth the implications of these models stress primarily two aspects. Firstly, the theoretical models suggest that centre and periphery might not converge to the same steady state, and we should therefore check for the existence of convergence clubs. Secondly, the theoretical approaches point at the significance of spillover effects and the relevance of their geographical range as regards the development of regional disparities. Geographic spillover effects might be considered explicitly by spatial regression models.

3. Methodological Aspects

Our methodology assumes that the core-periphery pattern considered by Fujita / Thisse (2002) as well as Ottaviano / Martin (1999) does not refer to the European scale as e.g. a corresponding scheme proposed by the EU Commission (2001).[3] In our opinion the approach is more appropriate to explain differences between highly agglomerated urban regions and rural peripheral areas. Therefore the empirical analysis investigates convergence among different spatial categories: agglomerated regions, urbanised regions and rural regions. This is in contrast to recent analyses of convergence among European regions by Fischer / Stirböck (2004) as well as Baumont et al. (2003). These authors also apply a spatial regimes approach, but define categories similar to the Eu-

2 See Galor (1996) for a survey of different models that generate club convergence.

3 EU Commission (2001), map A.4.

ropean core-periphery pattern suggested by the Commission. There is a second difference between our approach and the above mentioned convergence studies. Whereas they estimate both regime-specific intercepts and convergence rates, we only consider different intercepts by including corresponding dummy variables. More precisely, we use a set of country dummies in order to control for country-specific effects. Country specific factors have been found to be very influential on regional convergence processes in Europe (e.g. Armstrong, 1995). Thus, instead of determining convergence clubs by a spatial clustering of high and low income regions we emphasise the importance of national differences. With the inclusion of country dummies in the convergence estimation, we test regional convergence within countries rather than convergence between countries. Therefore, the regions are allowed to converge towards country-specific steady state levels of income.

In their cross-country growth analysis Durlauf/Johnston (1995) argue that economic theory provides no information on the number of regimes or on the way in which variables determine the different convergence clubs. Therefore they apply a data-sorting method in order to select the regimes endogenously. As Baumont et al. (2003) note, a corresponding methodology that takes into account spatial effects is not available yet. Moreover, the theoretical models outlined in section 2 provide some hints regarding the determination of convergence clubs. They imply the non convergence of per capita income of the centre and the periphery. The concept of convergence clubs is in line with such persistent disparities. Transferred to the European economic landscape, the theoretical framework suggests differentiating between highly agglomerated regions, being the origin of innovation and growth, on the one hand side and rural peripheral regions where no or only little R&D takes place on the other hand. The latter regions might benefit from growth and innovation initiated in the agglomeration, but they will not be able to catch up with the income level of agglomerations if spillovers are not global.

A common approach to investigate regional convergence is the traditional cross-sectional regression with income growth $\ln(y_{t+T}/y_t)$ as dependent variable and the initial level of income $\ln(y_t)$ as explanatory variable. We also include a number of dummy variables in order to account for national factors and effects specific to different region types. Using matrix notation, the corresponding conditional convergence model is given by:

$$(1) \qquad \frac{1}{T}\ln\left(\frac{y_{t+T}}{y_t}\right) = \alpha_0\iota + \alpha_1\ln(y_t) + S\gamma + \varepsilon \; .$$

Here S represents the matrix of country and region type dummies and γ is a vector of coefficients. There is conditional convergence if $\alpha_1 < 0$. The rate of convergence β can be obtained using the relation $\beta = -\ln(1 - \alpha_1 T)/T$. If $\varepsilon \sim NV(0, \sigma^2 I)$, OLS will be blue. Given that our data is a cross section of regions we might have three types of departures from this assumption: firstly, there might be heteroskedasticity; secondly, there might be spatial autocorrelation, and thirdly, there might be outliers and parameter heterogeneity. While the first deviation leads to OLS inefficiency, the last two might seriously bias the estimates.

To deal with all three issues we proceed in three steps: first we estimate OLS. Using the RESET and the White-test we check for misspecification and heteroskedasticity. To measure spatial autocorrelation in regression residuals, we use a number of different tests: a Moran test and Lagrange Multiplier tests (LM_{LAG}, LM_{ERR} and robust versions of tests). The Moran test effectively detects a spatial clustering of similar (and respectively dissimilar) values of the residuals. However, it does not distinguish alternative forms of ignored spatial dependence, whereas the different types of LM tests supply precise information about the kind of spatial dependence, i.e. whether spatial autocorrelation in the residuals stems from regional growth spillovers or, for instance, from a wrongly specified regional system (see Anselin / Rey, 1991; Anselin / Bera, 1998; Anselin / Florax, 1995). According to the results of these tests, different spatial models can be estimated if necessary, i.e. in case of a misspecification.[4]

Spatial effects are not accounted for explicitly in the regression model that we applied to investigate conditional convergence and convergence clubs. However, ignoring spatial dependence might result in serious econometric problems. A corresponding misspecification will be reflected by spatially autocorrelated residuals. Anselin / Rey (1991) differentiate between substantive spatial dependence and nuisance dependence. The latter refers to spatial autocorrelation that pertains to the error term and can be caused by measurement problems, such as a poor match between the spatial pattern of the analysed economic phenomenon and the units of observation. The substantive form of dependence can be induced by the various economic linkages that exist among neighbouring regions.

By estimating regression models that include spatial autocorrelation, we can allow for spillover effects that are a central feature of the theoretical models outlined in section 2. According to Fingleton (2003), spillovers are likely to carry across the borders of regions. Thus, there might be an impact of spillovers on growth in neighbouring areas which can be investigated using spatial econometric methods. Furthermore, spatial dependence of growth can be brought about by explanatory variables which are spatially autocorrelated. These might also involve country-specific factors, such as national policies or legislation, which have a common effect on all regions within national borders. As the results by Armstrong (1995) show, including country dummies is a way

[4] See Anselin (1988) for a detailed description of test statistics and spatial regression models.

to eliminate spatial error autocorrelation in convergence analyses. However, apart from including country dummies we also apply spatial regression models since we want to check whether spatial dependence is caused by spatial spillovers or bases solely on country effects. Two different approaches are used in order to investigate the significance of spillovers and country effects: the spatial error model and the spatial lag model.

The spatial error model will be appropriate if nuisance dependence causes spatially autocorrelated residuals. In this case, spatial dependence is restricted to the error term. Thus, on average income per capita growth is properly explained by the convergence hypothesis (see Anselin et al., 2000). Therefore, the OLS regression of equation (1) still yields unbiased estimates but statistical inference may be misleading. The corresponding regression model is given by:

$$(2) \qquad \frac{1}{T}\ln\left(\frac{y_{t+T}}{y_t}\right) = \alpha_0\iota + \alpha_1\ln(y_t) + S\gamma + \lambda Wu + \varepsilon = \alpha_0\iota + \alpha_1\ln(y_t) + S\gamma + (I-\lambda W)^{-1}\varepsilon \qquad u = \lambda Wu + \varepsilon \qquad \varepsilon \sim N(0,\sigma^2 I)$$

where ε is a vector of independently and identically distributed disturbances and λ is a spatial autoregressive parameter. W represents a spatial weight matrix that is supposed to capture the structure of the spatial dependence in the regional system. Thus, Wu is the weighted average of the errors in adjacent regions.

However, the OLS estimates will be biased, if the so-called substantive form of spatial dependence causes autocorrelated residuals in the convergence regression. The substantive form of spatial autocorrelation characterises economic phenomena that incorporate spatial interaction. All inference based on the traditional convergence regression will be incorrect. Instead, a spatial lag model, which includes a spatially lagged dependent variable on the right hand side, should be applied in this case to achieve proper results:

$$(3) \qquad \frac{1}{T}\ln\left(\frac{y_{t+T}}{y_t}\right) = \alpha_0\iota + \alpha_1\ln(y_t) + S\gamma + \rho W\ln\left(\frac{y_{t+T}}{y_t}\right) + u = (I-\rho W)^{-1}(\alpha_0\iota + \alpha_1\ln(y_t) + S\gamma) + (I-\rho W)^{-1}u$$

where ρ is the spatial autoregressive parameter of the spatially lagged dependent variable. The lag specification implies that the growth rate of a region is affected not only by its own initial income level, but likewise by the income growth and, therefore, the initial income level in adjacent regions. On average regional income growth is not solely explained by the local level of the initial income. But also, indirectly through the effect on income growth, by the income level everywhere in the regional system (see Anselin et al., 2000).

Finally, we have to consider that OLS and spatial regressions can be seriously biased by outliers. Given that measurement at the regional level is conceptually and practically difficult, mismeasurements seems to be likely. Therefore, the robustness to outliers is rather important in the regional context. Another problem arises if the influence of explanatory variables changes in the growth process. To deal with outliers and parameter heterogeneity we use quantile regressions as introduced by Koenker / Basset (1978) and surveyed by Koenker / Hallok (2001). The 0.5-quantile regression, i.e. the median regression, corresponds to least absolute deviation estimator and is, therefore, a robust alternative to OLS. Minimizing the distance to other quantiles than the median, gives an estimate for the marginal effects of a change in the independent variables at the particular point of the conditional distribution (see Buchinsky, 1998). Typically, quantile regressions have been applied to micro data. As an exception, Barreto / Hughes (2004) analyse convergence at the country level and find considerable parameter heterogeneity across the conditional distribution.

Quantile regressions minimize an objective function which is a weighted sum of absolute deviations:

$$\text{(4)} \qquad \min_{\beta \in k}\left[\sum_{i \in \{i: y_i \geq x_i\gamma\}} \tau |g_i - x_i\gamma| + \sum_{i \in \{i: y_i < x_i\gamma\}} (1-\tau)|g_i - x_i\gamma|\right].$$

Here $g_i = (\ln(y_{t+T}) - \ln(y_t))/T$ is the average annual growth rate and x_i is the vector of explanatory variables which is multiplied by the coefficients γ. The explanatory variables include country dummies, region types and initial income. The objective function can be interpreted as an asymmetric linear penalty function of deviations from predicted to actual growth rates. An important special case is the median regression ($\tau = 0.5$) which gives the least absolute deviations estimator. Since this regression puts less weight on outliers than OLS, it is a robust alternative. Further, complete quantile regression yields a family of coefficients; one for each sample quantile. Recent inferential procedures developed by Koenker / Xiao (2001) allow to test hypotheses on the entire conditional distribution of GDP per capita growth rates. This means that we are able to test, whether the marginal effects of a change in the independent variable are different at different quantiles of the distribution.

4. Data

The paper aims to investigate the significance of national factors, region types and spatial effects for growth and convergence in the EU. Starting from our theoretical considerations, we have to deal primarily with three types of effects:

- Country specific effects: economic policies, legislation and institutions tend to be the same for all regions within a specific country. However, they usually differ across countries. If policy and institutions in country A promote growth better than those in country B, country A should grow at a higher rate.
- Region type effects: agglomerations, urbanised and rural regions differ not only with respect to their population density. Among other things, they are also marked by different human capital endowments and R&D activity. Since these are important determinants of growth, the disparities may affect long-run growth and convergence. Hence, there might be systematic differences between growth rates of region types.
- Spatial effects: recent research emphasises the significance of spillover effects for economic growth. As the impact of spillovers might exceed regional boundaries, growth of neighbouring areas is possibly marked by spatial dependence.

The following data description is structured by the three different kinds of regional specific effects. We analyse the growth in 192 European regions over the period 1980 – 2002. The real regional per capita GDP (in prices of 1995) series are drawn from Cambridge Regional Economics data. The 192 NUTS 2 regions are form 15 EU countries: Austria AU (9), Belgium BE (11), Germany DE (30), Denmark DK (3), Spain ES (16), Finland FI (5), France FR (22), Greece GR (13), Ireland IE (2), Italy IT (20), Luxemburg LU (1), Netherlands NE (10), Portugal PT (5), Sweden SE (8), Spain ES (16), United Kingdom UK (37).

Differences in the growth experience of EU countries are well documented in the literature. Average annual growth rates between 1980 and 2002 are in the rage of 1.3 % in Greece and 4.8 % in Ireland. The box and whisker plot in Figure 1 shows the distribution of average annual growth rates across and within countries. For each country the box represents the middle half of the distribution of growth rates. The horizontal line represents the median growth rate. The whiskers display the lower and the upper quartile of the distribution. In cases where regions require whiskers exceeding 1.5 they are truncated and the remaining regions are displayed as outliers. Three things become apparent from Figure 1. Firstly, Ireland and Luxemburg are exceptions and systematically different from the other thirteen countries. Secondly, the variation of regional growth rates within most countries is far higher than the variation of median growth rates among the majority of countries. Thirdly, the plot reveals seven regions with growth rates that are compared to their country distribution unusually high or low.

In order to analyse whether agglomerations and rural regions converge to different steady states, we use a partition of EU regions into spatial categories. This classification is based on a typology of settlement structure established

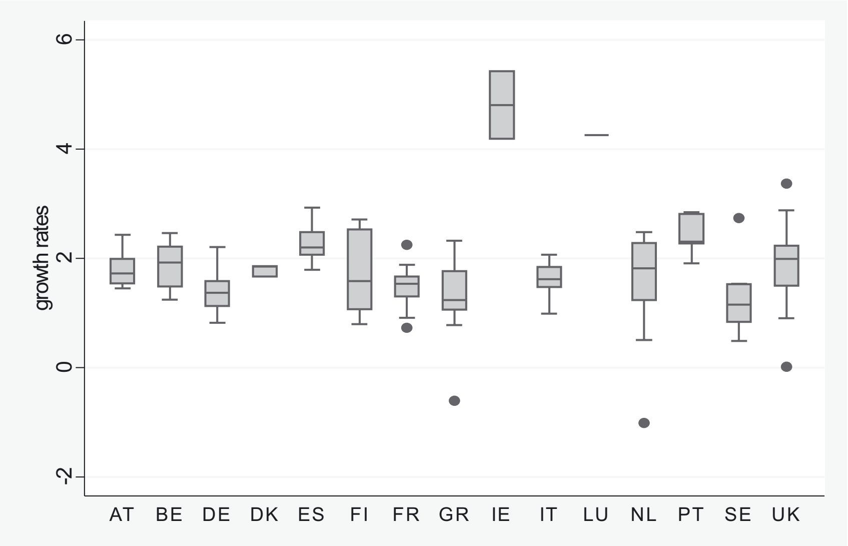

Figure 1: Box-Plot: Distribution of growth rates across countries

by the Study Program on European Spatial Planning.[5] Based on the criteria population density and size of regional centres three groups of regions (agglomerated, urbanised and rural regions) and six spatial categories have been defined (see Table 1). The highly agglomerated areas with a large centre (agglomerated regions, type 1) mainly comprise the capital regions of the EU member states. Moreover, this group includes regions with large economic centres as e.g. the Ruhr area, parts of northern Italy and southern Germany. Compared to type 1 the agglomerated regions of type 2 have a lower population density (between 150 and 300 inhabitants per km^2). They also contain some European capitals (Lisbon and the Stockholm region). Urbanised and agglomerated areas are first of all located in the core region of the EU, extending from the Southwest of the UK to Belgium, the Netherlands and West Germany. In contrast, rural areas concentrate in the periphery of the EU, i.e. especially the northern part of Sweden and Finland, Spain, Portugal and Greece. See Figure 2 for a map showing the distribution of different spatial categories in Europe.

5 See SPESP indicator set: http://www.bbr.bund.de/cln_005/nn_103086/DE/Raumbeobachtung/Werkzeuge/Raumabgrenzungen/Raumstruktur_Europa/Raumstruktur_Europa.html.

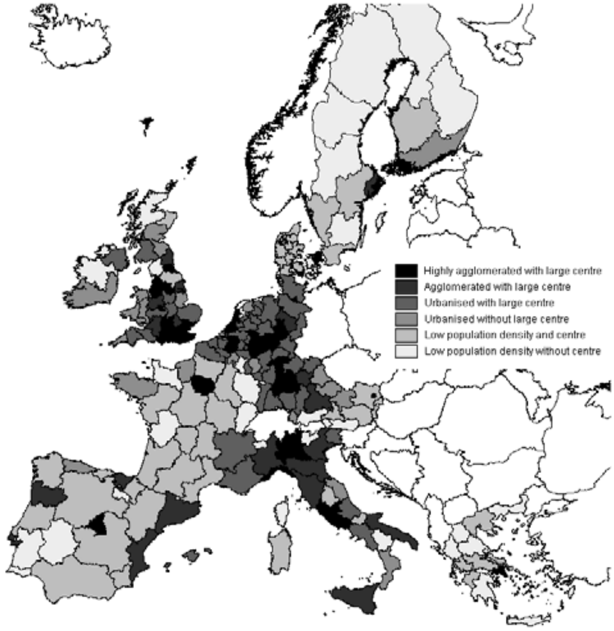

Figure 2: Distribution of region types over Europe

Table 1

Spatial categories according to settlement structure

Type	Spatial categories	Size of the regional centre (number of inhabitants)	Population density (inhabitants per km^2)
	Agglomerated regions		
1.1	Highly agglomerated with large centre	> 300.000	> 300
1.2	Agglomerated with large centre	> 300.000	150 up to 300
	Urbanised regions		
2.1	Urbanised with large centre	< 300.000 or > 300.000	> 150 (and a centre with < 300.000 inhabitants) or 100 up to 150 (and a centre with > 300.000 inhabitants)
2.2	Urbanised without large centre	< 300.000	100 up to 150
	Rural regions		
3.1	Low population density and centre	> 125.000	< 100
3.3	Low population density without centre	< 125.000	< 100

Figure 3 displays a box and whisker plot for the distribution of growth rates across different region types. According to the box plots there seems to be no systematic difference between growth rates of different region types. The median growth rates are at about the same level and they vary unsystematically between region types. In particular there is no tendency of rural or urbanised regions to grow faster than agglomerations. This indicates that the different region types might converge to different income levels. Within the unconditional framework, the box and whisker plots reveal 5 regions with unusually high or low growth rates.

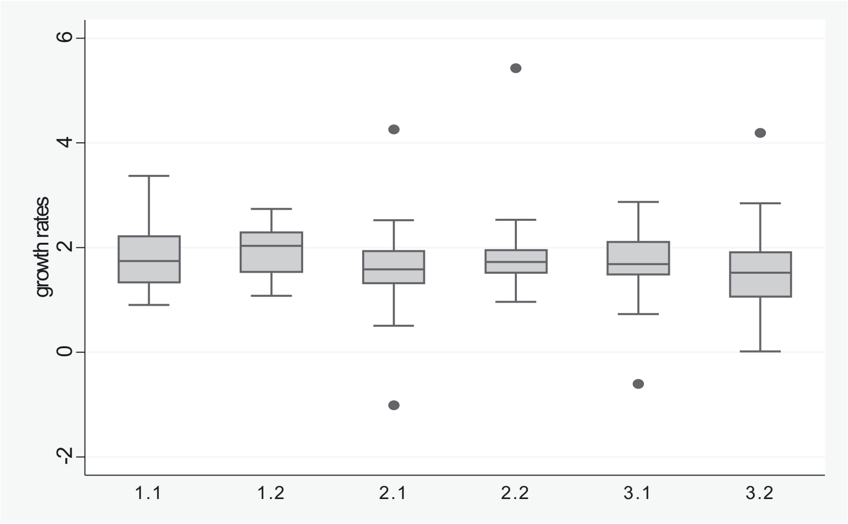

Figure 3: Box-Plot: Distribution of growth rates across region types

Finally, we consider the spatial dimension of regional growth and investigate the spatial autocorrelation of growth rates. Spatial autocorrelation describes the relation between the similarity of a considered indicator and spatial proximity. Anselin (1988) notes that it is generally taken to mean the lack of independence among observations in cross-sectional data sets. Thus, positive spatial autocorrelation implies a clustering in space. Similar growth rates, either high or low, are more spatially clustered than could be caused by chance.

Measures of spatial autocorrelation take into account the various directions of dependence by a spatial weights matrix W. For a set of R observations, the matrix W is a $R \times R$ matrix whose diagonal elements are set to zero. The matrix specifies the structure and intensity of spatial effects. Hence, the element w_{ij} represents the intensity of effects between two regions i and j (see Anselin / Bera, 1998). A frequently applied weight specification is a binary spatial weight matrix such that $w_{ij} = 1$ if the regions i and j share a border and $w_{ij} = 0$ otherwise. We apply two additional concepts for spatial distance: In the first, we use the inverse of travel time between region's capitals for w_{ij}. In the second, we use the inverse of travel time for regions within the same country and set $w_{ij} = 0$ for regions located in different countries. Table 2 presents the tests for spatial autocorrelation for regional growth, the log of initial income and for the region types. The results indicate considerable spatial autocorrelation in European regional growth and its potential determinants.

Table 2

Spatial correlation

Variable	Travel Time		Travel Time cut at border		Binary	
	Moran's I	Geary's c	Moran's I	Geary's c	Moran's I	Geary's c
$(\ln(y_{t+T}) - \ln(y_t))/T$	0.054 (8.993)	0.901 (–3.276)	0.412 (13.458)	0.588 (–10.543)	0.179 (3.473)	0.803 (-2.842)
$\ln(y_t)$	0.206 (31.432)	0.737 (–16.71)	0.704 (22.453)	0.281 (–21.522)	0.468 (8.78)	0.556 (–7.686)
Region type	0.098 (15.335)	0.882 (–10.7)	0.334 (10.7)	0.679 (–9.966)	0.294 (5.538)	0.699 (–5.43)

z-ratios in parentheses.

5. Regression Results

We start with a general specification of the convergence regression including dummies for all countries as well as for regions and sub region types. The dependent variable is the average annual GDP per capita growth in percent. Table 3 gives the results for the OLS regression over the sample period 1980 to 2002. The lower part of the table gives some regression diagnostics. Since these indicate heteroskedastisity, we compute robust standard errors. The coefficient of initial income is significantly negative. The dummies for urbanised and rural regions (R2 and R3) are both significant and imply a lower steady state income level compared to agglomerations. However, the dummies for the sub-regions (i.e. R1.2, R.2.2., R3.2) are insignificant. Considering the country effects the OLS regression shows 5 countries (AT, BE, DK, IE, LU) with significant positive coefficients, which implies a higher steady state income level than in the reference country Germany. For Greece (GR) we obtain a negative coefficient. In the lower part of the table the regression diagnostics are given. Here the RESET and the White test indicate omitted variables or misspecification. The Lagrange Multiplier tests (LM) and Robust Lagrange Multiplier tests (RLM) indicate that there are no spatially autocorrelated residuals. Only Moran's I points to spatial autocorrelation. However, results by Anselin / Rey (1991) suggest that the Moran statistic picks up a range of misspecification errors, such as non-normality and heteroskedasticity and might therefore provide unreliable inference. To assure that the non-correlation of errors does not depend on the specific form of the spatial weights matrix chosen, we use two alternative measures for distance and binary weights. The tests of spatial correlation are recalculated with the binary weights matrix and with the distance matrix cut off at the borders. In both cases we cannot find significant spatial autocorrelation in the error terms.

Table 3

Results of the general specification*

$\ln(y_t)$ –0.833 (2.37)	R1.2 –0.074 (0.47)	R2 –0.277 (1.91)	R2.2 –0.013 (0.11)	R3 –0.396 (1.96)	R3.2 –0.095 (0.72)
AT 0.486 (3.79)	BE 0.262 (1.63)	DK 0.577 (4.2)	ES 0.32 (1.12)	FI 0.489 (1.25)	FR 0.077 (0.56)
GR –0.636 (1.58)	IE 2.829 (5.19)	IT –0.182 (0.83)	LU 2.884 (38.55)	NL 0.063 (0.21)	PT 0.118 (0.25)
SE 0.081 (0.31)	UK –0.021 (0.08)	const 9.777 (2.78)			

t-ratios in parentheses.

Regression diagnostics:	$R^2 = 0.52$.
RESET:	F(3, 168) = 9.64; White chi2(73) = 131.41; BP: chi2(1) = 5.14.
Spatial error:	Moran's I = 7.92 (0); LM = 0.84 (0.36); LM = 0.057 (0.81).
Spatial lag:	LM = 0.79 (0.38); RLM = 0.002 (0.97).

* The dependent variable is the average annual growth rate in percent.

Before we further investigate the question of spatial autocorrelation we eliminate insignificant variables to reach a more parsimonious specification. The OLS estimation results for the parsimonious specification are given in column 2 of Table 4. The regressions diagnostics in the lower part of the table again point to some misspecification. The Lagrange Multiplier tests for spatial autocorrelation indicate no correlation of residuals. Still we estimate the spatial lag and the spatial error model to check for the robustness of our results. The estimates are given in columns 3 and 4 of Table 4. The coefficient of the initial income level is always significantly negative and, therefore, evidence of conditional convergence is fairly robust. The estimated speed of convergence is just below 1 %. Furthermore, the findings imply convergence to lower steady state levels for urbanised and rural areas and significant country effects. In contrast, evidence of spatial effects is rather weak. In the spatial lag specification, the coefficient ρ of the spatially lagged dependent variable is not significant. The coefficient λ of the spatial error specification is not significant at the 5 % level as well. According to unreported regression results country-specific effects capture the spatial dependence that marks regional growth of GDP per capita. Whereas the omission of county dummies leads to considerable spatial autocorrelation, removal of the region type effects does not induce a misspecification due to ignored spatial effects.[6]

Table 4

Regression results*

	OLS	Spatial lag	Spatial error
$\ln(y_t)$	–0.872 (6.44)	–0.811 (6.64)	–0.879 (7.54)
R2	–0.258 (2.66)	–0.240 (2.61)	–0.275 (2.81)
R3	–0.322 (3.09)	–0.313 (3.34)	–0.346 (3.57)
AT	0.392 (4.29)	0.390 (2.25)	0.353 (1.89)
BE	0.214 (1.77)	0.209 (1.35)	0.206 (1.19)
DK	0.488 (5.06)	0.496 (1.70)	0.489 (1.67)
GR	–0.818 (4.22)	–0.711 (3.66)	–0.756 (3.97)
LU	2.851 (34.39)	2.870 (5.80)	2.879 (5.88)
IE	2.681 (5.52)	2.670 (7.53)	2.701 (7.51)
IT	–0.280 (3.27)	–0.248 (1.99)	–0.303 (2.19)
Const.	8.897 (7.46)	8.897 (5.34)	10.256 (9.15)
rho / lambda		0.393 (0.95)	0.636 (1.93)
R^2	0.502	0.503	0.505

t-ratios in parentheses.

Diagnostics of the OLS Regression
RESET: F(3, 179) = 7.89; White chi2(27) = 37.07; BP: chi2(1) = 2.96.
Spatial error: Moran's I = 5.28 (0); LM = 1.91 (0.17); RLM = 1.70 (0.19).
Spatial lag: LM = 0.61 (0.43); RLM = 0.39 (0.53). *p*-values in parentheses.

* The dependent variable is the average annual growth rate in percent.

6 Corresponding results are available from the authors upon request.

Finally, even though the results of most coefficient estimates are remarkably stable over the different specifications there remains some doubt: for all specifications regression diagnostics indicate heteroskedasticity or misspecification. The examination of standardised residuals reveals several outliers. These might be the reason for the misspecification indicated by the regression diagnostics. Since outliers can seriously bias OLS estimates, a more robust regression technique is warranted.

In order to deal with the effects of outlying observations, we apply quantile regressions. We start with the median regression, i.e. with the regression that gives the least absolute deviations estimator and, therefore, the robust alternative to OLS.[7] Again, we first estimate the general model including all country dummies and sub region types as explanatory variables. Then we eliminate all insignificant variables. We turn up with the same set of country dummies as with OLS, and the sub region dummies are not significant. The results are given in Table 5. In addition the table displays the results for regressions minimising the weighted sum of deviations to the 10th, 25th, 75th and 90th quantile.

According to the median regression given in column 4 of Table 5, the same explanatory variables as with OLS are significant. Furthermore, the marginal effects of these variables on the regional growth rates are in the same order of magnitude. The initial income level is significantly negative and so there is conditional convergence. The region type effects are significant, implying that urbanised and rural regions converge to lower steady state levels than agglomerations. Overall, the median quantile estimator is rather similar to the OLS. This result is quite reassuring since it means that the regression minimizing the distance to the conditional mean leads to similar results as the regression minimizing the distance to median. Since the median regression is robust to outliers, we can note that there is no serious bias caused by outliers.

Now consider the estimates at other parts of the conditional distribution. The comparison of results for different quantiles reveals that not all of the explanatory variables are significant over all quantiles. However, the coefficient for the initial income is significantly negative in all quantile regressions. Accordingly, even for regions where the model underestimates the growth rate and for those regions where the model overestimates the growth rate, there is convergence. The influence of region types differs across the different quantiles. At the 10th quantile, urbanised and rural areas are not significantly different to agglomerations. Hence, poor growth performance – relative to our model – appears independent of the settlement structure.

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7 For an overview on quantile regressions see Buchinsky (1998).

Table 5

Quantile regressions*

	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
$\ln(yt)$	–1.051 (3.94)	–1.039 (5.67)	–0.826 (7.88)	–0.965 (5.78)	–0.579 (1.91)
R2	0.002 (0.01)	–0.261 (1.7)	–0.297 (3.94)	–0.235 (1.55)	–0.305 (1.64)
R3	–0.261 (1.05)	–0.278 (1.96)	–0.304 (3.81)	–0.336 (2.52)	–0.225 (0.75)
AT	0.729 (5.73)	0.558 (4.99)	0.31 (2.74)	0.411 (2.9)	–0.053 (0.22)
BE	0.165 (0.7)	0.058 (0.22)	0.334 (1.7)	0.255 (1.63)	–0.047 (0.27)
IT	–0.217 (1.0)	–0.148 (1.15)	–0.313 (5.26)	–0.371 (3.04)	–0.546 (3.01)
DK	1.176 (3.85)	0.759 (3.66)	0.414 (3.2)	0.381 (2.61)	–0.304 (0.95)
GR	–0.852 (1.98)	–0.934 (3.64)	–0.886 (4.80)	–0.667 (2.07)	–0.662 (2.09)
IE	2.552 (2.16)	2.15 (1.96)	2.006 (1.77)	3.064 (2.82)	2.875 (2.77)
LU	3.354 (2.08)	3.184 (2.14)	2.848 (2.12)	2.647 (2.13)	2.158 (2.1)
Const.	11.156 (4.43)	11.465 (6.38)	9.764 (9.72)	11.255 (7.04)	8.049 (2.79)
R^2	0.234	0.249	0.300	0.305	0.349

The t-ratios in parentheses are based on standard errors bootstrapped with 200 replications.

* The dependent variable is the average annual growth rate in percent.

Conclusions

Our results confirm the empirical evidence provided by a number of convergence studies: income growth of European regions is characterised by convergence. Moreover, the findings are in line with recent theoretical literature which combines endogenous growth with an NEG framework. According to these models we might observe convergence clubs. More precisely, agglomerations and rural peripheral regions possibly converge towards different steady state equilibria. The findings of the present study suggest a lower steady state income level for urbanised and rural areas of the EU than for highly agglomerated regions. At first sight this evidence seems to conflict with recent empirical evidence provided by Baumont et al. (2003) as well as Fischer / Stirböck (2004). These authors identify convergence clubs that refer to centre and periphery at the European scale. In contrast, our differentiation applies to a lower spatial scale and distinguishes agglomerations, urbanised and rural regions. However, there are some similarities among both concepts. The incidence of spatial categories is linked to the location in the centre and periphery at the European scale. Whereas rural areas are mainly located in the periphery of the EU, urbanised regions and agglomerations concentrate in the core region of Europe.

With respect to the significance of spatial dependence of regional growth caused by spillover effects which affect income growth in neighbouring regions, the evidence in our study is rather weak. Spatial autocorrelation seems to be mainly due to country-specific effects. Therefore, regarding the importance of national factors as opposed to spatial-spillover factors we do not agree with the assessment by Quah (1996), who concludes that spatial spillover factors matter more than national factors. Spatial effects have undoubtedly significant growth effects. But much of the spatial dependence that marks regional growth in Europe seems to base on differences in national policies, legislation and institutions. However, there might be important short-distance spillovers and growth dependencies among neighbouring regions that we can not observe at our level of spatial aggregation.

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