Regional convergence clubs in Europe: Identification and conditioning factors

Monika Bartkowska[a,*], Aleksandra Riedl[a,b,**]

[a] *Institute for Economic Geography and GIScience, Vienna University of Economics and Business, Nordbergstrasse 15, 1090 Vienna, Austria*
[b] *CESifo, Poschingerstrasse 5, 81679 Munich, Germany*

Abstract

The aim of this paper is to empirically identify convergence clubs in per capita incomes of European regions and to investigate whether initial conditions — as suggested by the club convergence hypothesis — are responsible for club formation. To tackle this issue, we propose a two-step procedure in which we first endogenously identify groups of regions that converge to the same steady state level, and in a second step we investigate the role of starting conditions and structural characteristics for a region's club membership. Our sample comprises 206 European NUTS2 regions between 1990 and 2005. The results strongly support the existence of convergence clubs, indicating that European regions form five separate groups converging to their own steady state paths. Moreover, estimates from an ordered probit model reveal that the level of initial conditions such as human capital and per capita income plays a crucial role in determining the formation of convergence clubs among European regions.

Keywords: club convergence hypothesis, conditioning factors, European regions, spatial filtering, log t test, probit model

JEL classification: C23; F02; O40; R11

[*] Corresponding author. E-mail address: monika.bartkowska@wu.ac.at, Phone: 0043 1 31336 5731, Fax: 0043 1 31336 703; Date of birth: 7^{th} November 1981

[**] E-mail address: aleksandra.riedl@wu.ac.at; Date of birth: 10^{th} June 1977

October 12, 2009

1. Introduction

One class of growth theories (e.g., Azariadis and Drazen, 1990; Galor, 1996) shows that economies which are rather similar in their structural characteristics (e.g., production technology, preferences, government policies, etc.) may nevertheless converge to different steady state equilibria if they differ in terms of initial conditions. Hence, within a group of similar economies, a common balanced growth path can only be expected if their initial conditions are in the basin of attraction of the same steady state equilibrium — a phenomenon widely referred to as the *club convergence* hypothesis. Accordingly, economies that approach the same steady state equilibrium are said to form a convergence club (Galor, 1996).

In seeking to test the *club convergence* hypothesis, researches have devoted a great deal of effort to developing the appropriate econometric tools. By means of regression tree analysis, Durlauf and Johnson (1995) identify groups of countries according to the initial conditions suggested by Azariadis and Drazen (1990), namely an economy's initial level of income and human capital. They find that convergence rates (β-convergence) within the groups are larger than in the overall sample, which can be interpreted as an indication of the presence of multiple regimes.[1] However, if the task is to identify convergence clubs, approaches which group economies a priori face the limitation that the cluster outcomes are to some extent predetermined. First, one has to specify the variable(s) responsible for club formation and, in a second step, arbitrarily determine its threshold level(s).

Recently, an increasing amount of literature has emerged concerning the identification of convergence clubs via endogenized grouping, that is, by leaving factors unspecified that are responsible for the appearance of multiple steady states (e.g., Bernard and Durlauf, 1995; Hobijn and Franses, 2000; Phillips and Sul, 2007). Besides the advantage of overcoming the aforementioned drawback, these methods focus on the cross-sectional distribution of income (σ-convergence) rather than on β-convergence. This is crucial because the latter concept is based on the *within* dimension of an economy and thus cannot reveal whether economies indeed converge toward one another (e.g., Islam, 2003 and Quah, 1993). In fact, there is a basic consensus that the distribution of income per capita across economies exhibits cluster patterns rather than a common growth path (e.g., Phillips and Sul, 2009; Mora, 2005; Burkhauser et al., 1999; Desdoigts, 1999 and Quah, 1996a). Interestingly, this phenomenon does not apply exclusively to heterogeneous samples such as economies across different continents, but it has also been observed in fairly integrated markets such as those in Western Europe (Corrado et al., 2005).

Yet, even though methods of endogenous grouping can identify convergence clubs they cannot confirm whether these clubs can, in fact, be attributed to theories that generate the *club convergence* hypothesis. In particular, it is not possible to assess which factors led to the multiplicity of steady state equilibria. If only structural characteristics are responsible for the cluster outcome, the evidenced patterns may be interpreted wrongly

[1] β-convergence is investigated by employing growth-initial level regressions where the coefficient on the initial income variable provides information on the extent of convergence.

as *club convergence* in cases where *conditional convergence* applies. According to the latter concept, economies with identical structural characteristics will converge regardless of their initial conditions (Solow, 1956). Hence, it is empirically difficult to distinguish *club convergence* from *conditional convergence*.

Against this background, the aim of this paper is to examine which factors are the driving force behind the formation of multiple steady states of per capita incomes across western European regions. In particular, we investigate whether initial conditions put forward by a certain class of theoretical models (e.g., Azariadis and Drazen, 1990) are indeed responsible for the observed convergence clubs. In order to address this issue, we propose a two-step procedure in which we first endogenously identify groups of regions that converge to the same steady state level and, in a second step, we investigate the role of starting conditions for club membership while controlling for the regions' structural characteristics. Our approach is most closely related to the work of Corrado et al. (2005), who analyze per capita income across European NUTS1 regions (where NUTS stands for Nomenclature of Territorial Units for Statistics). In their study, convergence clubs are determined endogenously using cointegration tests proposed by Hobijn and Franses (2000). In order to describe the resulting cluster patterns, they employ a multivariate cluster correlation analysis. However, our paper deviates from their study in three important aspects.

First, we employ a novel regression based convergence test developed by Phillips and Sul (2007), referred to below as the log t test, which is based on the cross-sectional variance ratio of per capita incomes over time. The advantage of such an approach is that it does not require the respective time series to be cointegrated and therefore allows individual behavior to be transitionally divergent. In effect, rejecting cointegration does not necessarily imply the absence of comovement or convergence (see section 2.1 and Phillips and Sul, 2007, p. 1779). Additionally, the suggested method makes it possible to endogenously reveal a broad spectrum of transitional behavior among economies, such as convergence to a common steady state, divergence and club convergence. Since the applied convergence test requires observations to be independent across sample units, we use spatial filtering techniques (Getis, 1995) to remove the spatial component inherent in regional data on per capita incomes.

Second, rather than describing the observed clusters, we employ an ordered regression model to analyze the relative importance of different growth determinants for a region's club membership. This allows us to disentangle the role of structural characteristics and initial conditions for the formation of convergence clubs. Among other things, we test whether the probability of belonging to a certain club is determined by a region's initial level of human capital and per capita income, as suggested by Azariadis and Drazen (1990).

Finally, our analysis is based on per capita income data on 206 NUTS2 regions in the period from 1990 to 2005. We choose this aggregation level because it corresponds to the European Union's classification of regions according to which structural funds are redistributed. These funds are provided as a means of reducing economic disparities across European regions and amount to 35.7% of the EU budget for the years 2007-2013. Hence, knowing the factors that give rise to multiple steady states among European NUTS2 regions is of particular relevance with regard to policy.

Our results reveal that European regions form five separate groups converging to their own steady state paths. Moreover, by controlling for structural characteristics of the regions, we show that starting conditions such as a region's initial level of human capital and per capita income, can indeed explain to which club it will belong. Hence, we can conclude that initial conditions, as suggested by the *club convergence* hypothesis, play a crucial role in determining a region's equilibrium steady state level.

The remainder of the paper is structured as follows: In section 2, we describe the method used to identify convergence clubs and provide the corresponding cluster results. In section 3, we discuss the main factors explored by growth literature which potentially determine the formation of convergence clubs and test their empirical relevance by means of an ordered regression model. Section 4 concludes.

2. Club identification

2.1. The log t test

In order to analyze the transitional behavior of per capita income among European regions over the 1990-2005 period, we apply the log t test developed by Phillips and Sul (2007). Income per capita is measured in terms of gross value added (GVA) per worker (at constant 2000 prices) on the basis of data obtained from the Cambridge Econometrics Database (CED). The test is based on an innovative decomposition of the variable of interest. Usually panel data are decomposed in the following way:

$$\log y_{it} = \varphi_i \mu_t + \epsilon_{it} \tag{1}$$

where φ_i represents the unit characteristic component, μ_t the common factor and ϵ_{it} the error term. In contrast, in the specification applied here, the log of income per capita, $\log y_{it}$, has a time-varying factor representation that can be derived from the conventional panel data representation:

$$\log y_{it} = \left(\varphi_i + \frac{\epsilon_{it}}{\mu_t} \right) \mu_t = \delta_{it} \mu_t \tag{2}$$

where δ_{it} absorbs the error term and the unit-specific component thus representing the idiosyncratic part that varies over time. While the first model attempts to explain the behavior of the individual $\log y_{it}$ by the common factor μ_t and two unit characteristic components, φ_i and ϵ_{it}, the second approach seeks to describe income per capita by measuring the share (δ_{it}) of the common growth path (μ_t) that economy i undergoes. In order to model the transition coefficients δ_{it}, a relative transition coefficient, h_{it}, is constructed:

$$h_{it} = \frac{\log y_{it}}{N^{-1} \sum_{i=1}^{N} \log y_{it}} = \frac{\delta_{it}}{N^{-1} \sum_{i=1}^{N} \delta_{it}} \tag{3}$$

such that the common growth path is eliminated. Hence, h_{it} represents the transition path of economy i relative to the cross-section average and has a twofold interpretation: First, it measures individual behavior in relation to other economies, and second, it describes the relative departures of economy i from the common growth path μ_t. In the case of convergence, that is, when all economies move toward the same transition path, $h_{it} \to 1$ for all i as $t \to \infty$. Then, the cross-sectional variance of h_{it}, denoted by $V_t^2 = N^{-1} \sum_i (h_{it} - 1)^2$, converges to zero. In the case of no convergence, there are a number of possible outcomes. For example, V_t may converge to a positive number, which is typical of club convergence, or remain bounded above zero and not converge or diverge.

In order to specify the null hypothesis of convergence, Phillips and Sul (2007) model δ_{it} in a semiparametric form:

$$\delta_{it} = \delta_i + \frac{\sigma_i \xi_{it}}{L(t) t^{\alpha}} \tag{4}$$

where δ_i is fixed, σ_i is an idiosyncratic scale parameter, ξ_{it} is iid(0,1), $L(t)$ is a slowly varying function (such that $L(t) \to \infty$ as $t \to \infty$) and α is the decay rate.[2]

The null hypothesis of convergence can be written as:

$$H_0 : \delta_i = \delta \text{ and } \alpha \geq 0 \tag{5}$$

and it is tested against the alternative $H_A : \delta_i \neq \delta$ for all i or $\alpha < 0$. Note that under the null hypothesis of convergence various transitional patterns of economies i and j are possible, including temporary divergence, which refers to periods where $\delta_i \neq \delta_j$. As a result, the method proposed by Phillips and Sul (2007) enables us to detect convergence even in the case of transitional divergence, where other methods such as stationarity tests (e.g., Hobijn and Franses, 2000) fail. In particular, stationary time series methods are unable to detect the asymptotic comovement of two time series and thus erroneously reject the convergence hypothesis.[3]

Considering equation (4), Phillips and Sul (2007) show that under convergence the cross-sectional variance of h_{it} has the limiting form

$$V_t^2 \sim \frac{A}{L(t)^2 t^{2\alpha}} \text{ as } t \to \infty \text{ for some } A > 0 \tag{6}$$

from which the following regression based convergence test can be deduced:

$$\log\left(\frac{V_1^2}{V_t^2}\right) - 2\log L(t) = a + b\log t + u_t$$
$$\text{for } t = [rT], [rT]+1, \ldots, T \tag{7}$$

where in general $r \in (0,1)$ and $L(t)$ is a slowly varying function. Based on Monte Carlo simulations, Phillips and Sul (2007) suggest using $L(t) = \log t$ and $r = 0.3$ for sample sizes below $T = 50$. Finally, using $\hat{b} = 2\hat{\alpha}$, a one-sided t-test robust to heteroskedasticity and autocorrelation (HAC) is applied to test the inequality of the null hypothesis $\alpha \geq 0$. The

[2]For details on regularity conditions concerning σ_i and ξ_{it}, see Phillips and Sul (2007), pp. 1786-1787.
[3]For details, see Phillips and Sul (2007), pp. 1778-1780, and Phillips and Sul (2009), subsection 4.1.

null hypothesis of convergence is rejected if $t_{\hat{b}} < -1.65$ (5% significance level).

If convergence is rejected for the overall sample, the testing procedure is applied to subgroups following a clustering mechanism test procedure suggested in Phillips and Sul (2007). The test consists of four steps which can be summarized as follows (for a precise description, see Appendix B.1): First, the units are sorted in descending order on the basis of the last period in the time series dimension of the panel. Then by means of the log t test a convergence club is formed. More precisely, this is accomplished by adding regions one by one to a group of the two highest-income regions at the beginning and running the log t test until the $t_{\hat{b}}$ for this group is larger than -1.65. Next, the log t test is repeated for this group and all of the units (one by one) remaining in the sample to check whether they converge. If not, the first three steps are applied to the remaining units. If no clubs are found, one may conclude that those units diverge.

2.2. *Spatial filtering*

In order to subdivide countries into smaller entities (e.g., regions), one would ideally classify them according to economic activities that are characteristic for a region. However, as NUTS2 regions are defined according to formal rather than functional criteria, we expect per capita income, y_i, to exhibit spatial autocorrelation. Indeed, the Moran's I test statistic for the year 2005 is equal to 0.6, indicating high spatial dependence in the variable of interest (e.g., Anselin, 1988). Therefore, before running the log t test, we apply Getis' filter in order to eliminate the spatial component inherent in the data (Getis, 1995; Getis and Griffith, 2002).[4]

According to Getis' filtering procedure, the spatially dependent variable is divided into a filtered nonspatial variable and a residual spatial variable. First, we identify the distance d for which the spatial autocorrelation statistic proposed by Getis and Ord (1992), $G_i(d)$, stops increasing and starts decreasing, where

$$G_i(d) = \frac{\sum_j w_{ij}(d) y_j}{\sum_j y_j}, \quad i \neq j \tag{8}$$

with w_{ij} equal to one for every connection between unit i and unit j within d (and $i \neq j$). At this point, the limit on spatial autocorrelation is assumed to have been reached, and the critical d value is found. The filtered observation, $\tilde{y}_i$, then takes the form

$$\tilde{y}_i = \frac{y_i \left[W_i/(n-1) \right]}{G_i(d)} \tag{9}$$

where W_i is the sum of all geographic connections w_{ij} and n denotes the number of observations in the sample. The data is filtered annually, that is, the distances maximizing the G_i statistic are allowed to vary over the time span.

[4] Note that, before applying the spatial filtering procedure, we first filter the data to remove the business cycle using the Hodrick-Prescott smoothing filter (Hodrick and Prescott, 1997) as suggested by Phillips and Sul (2007).

2.3. Regional convergence clubs

When the log t test[5] is applied to per capita incomes across 206 European NUTS2 regions over the 1990-2005 period, the hypothesis of overall convergence is rejected at the 5% significance level. Hence, we can conclude that European regions did not converge to the same steady state equilibrium in terms of per capita incomes. We then proceed to the clustering mechanism test procedure, where we identify 10 clusters and three diverging regions. Finally, to test whether any of the original subgroups can be merged to form larger convergence clubs, we apply the merging test procedure outlined in Appendix B.2. After a further pass through the data, five convergence clubs are identified. A list of the members of each club is provided in Appendix C. The results of the log t test are presented in table 1, where we report the estimated parameters and the corresponding standard errors together with the average per capita income of the regions belonging to the same club for the year 2005. In addition, we provide a graphic illustration of club membership in figure 1.

Table 1: Convergence club classification

Club	No. of regions	$\widehat{b}$	s.e.	Income per capita
Club 1	33	-0.1874	(0.1207)	64,000
Club 2	111	-0.1238	(0.0841)	48,000
Club 3	40	-0.0383	(0.0663)	40,000
Club 4	19	0.0471	(0.1639)	30,000
Club 5	3	0.4299	(0.0673)	18,000

Income per capita is measured by GVA per worker (in euros).

A few regularities are visible in the European convergence clubs obtained here. First, there is an apparent country effect, that is, regions belonging to the same country tend to cluster together (Barro and Sala-i-Martin, 1991 and Quah, 1996b). This applies most notably to Switzerland, but also to Austria, France and the Netherlands. Second, regions which include the capital city of the respective country appear to belong to a higher club than the neighboring regions, for instance Attiki (including Athens), Île de France (including Paris), Inner London, Lisbon and Vienna. This could be due to agglomeration effects, as presented by Martin and Ottaviano (2001), to name one example.

Interestingly, the clubs seem to be spatially concentrated, that is, regions belonging to the same club tend to cluster together. This is confirmed by the Moran's I test statistic, which is equal to 0.5 when applied to the club category variable. Given that the data was spatially filtered before the convergence test was applied, the spatial dependence among the clubs is likely to be of substantive nature. In particular, it could be driven by factors like informational externalities or knowledge spillovers (Quah, 1996b).

The influence of cohesion funds on club membership is ambiguous. On the one hand, there are regions that received such funds and nevertheless remained in the fourth and fifth clubs, especially regions from Southern Europe (e.g., Greece, Portugal and Spain). This seems consistent with Dall'erba and Le Gallo (2008), who find that structural funds

[5]The log t test, the clustering mechanism test procedure and the Getis' filter are programmed in Matlab. The codes are available upon request from the authors.

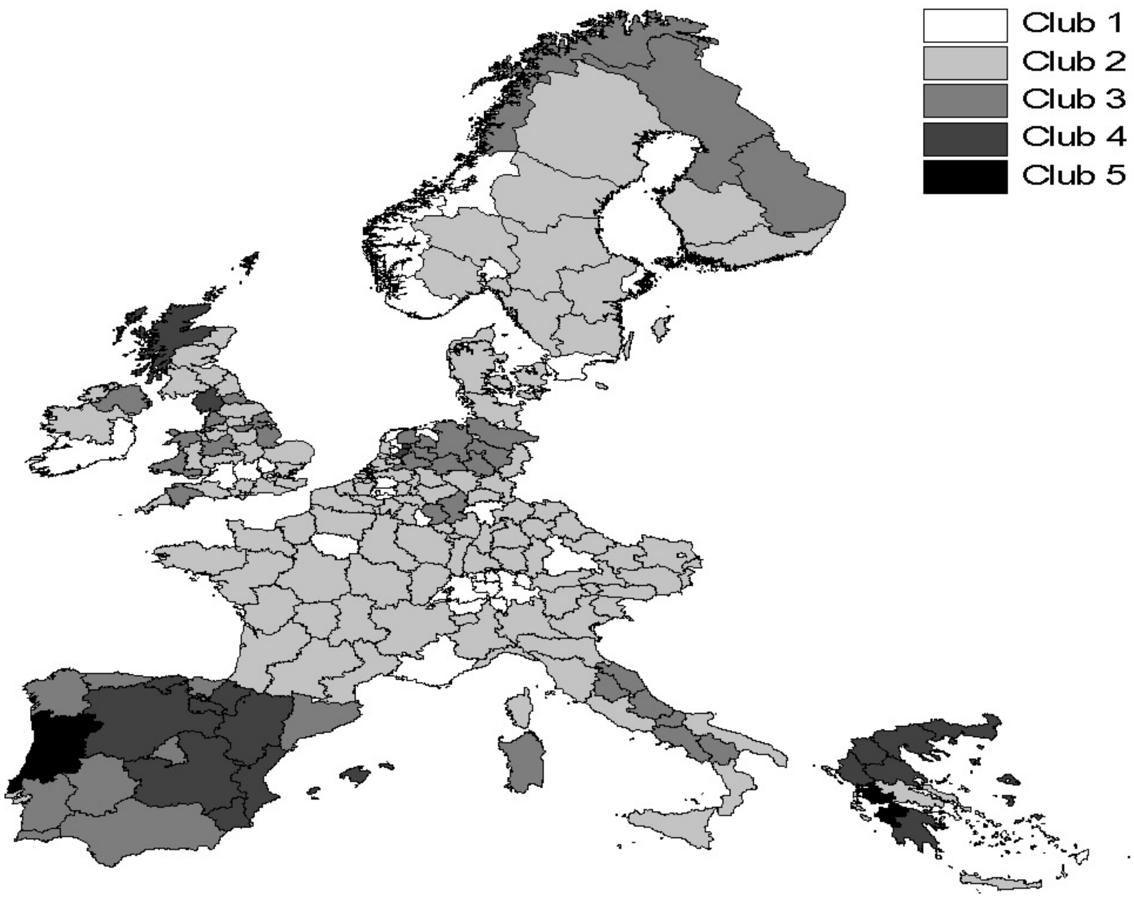

Figure 1: Convergence clubs

have no significant impact on the economic performance of regions. On the other hand, some initially poor regions such as Attiki or South and Eastern Ireland have managed to take off and now belong to the first club. Again, these are regions where the country's capital city is located. Our visual and loose analysis is supplemented by a more formal investigation in section 3.2.

Next, we employ a test to explore development tendencies across groups. Using the log t test, we check whether the λ_1 fraction of the lower-income members in the upper club and the λ_2 fraction of the higher-income members in the lower club converge. We set $\lambda_1 = \lambda_2 = 0.5$. The test for convergence between the subsequent clubs does not allow us to reject the convergence hypothesis for any of the pairs. There is ambiguity concerning the interpretation of such a result. First, it could indicate that regions which now belong to different clubs are slowly converging toward each other. However, the transition paths of the five clubs displayed in figure 2 do not seem to confirm such an assumption, as — after getting closer in the mid 1990s — the transition paths appear to move away from each other. Second, it could simply point to rather blurred borders between the clubs, as some regions might already be in transition toward a higher or a lower club. Interestingly, Phillips and Sul (2009) find similar results in an analysis of transitional behavior in per capita incomes across 152 countries from 1970 to 2003.

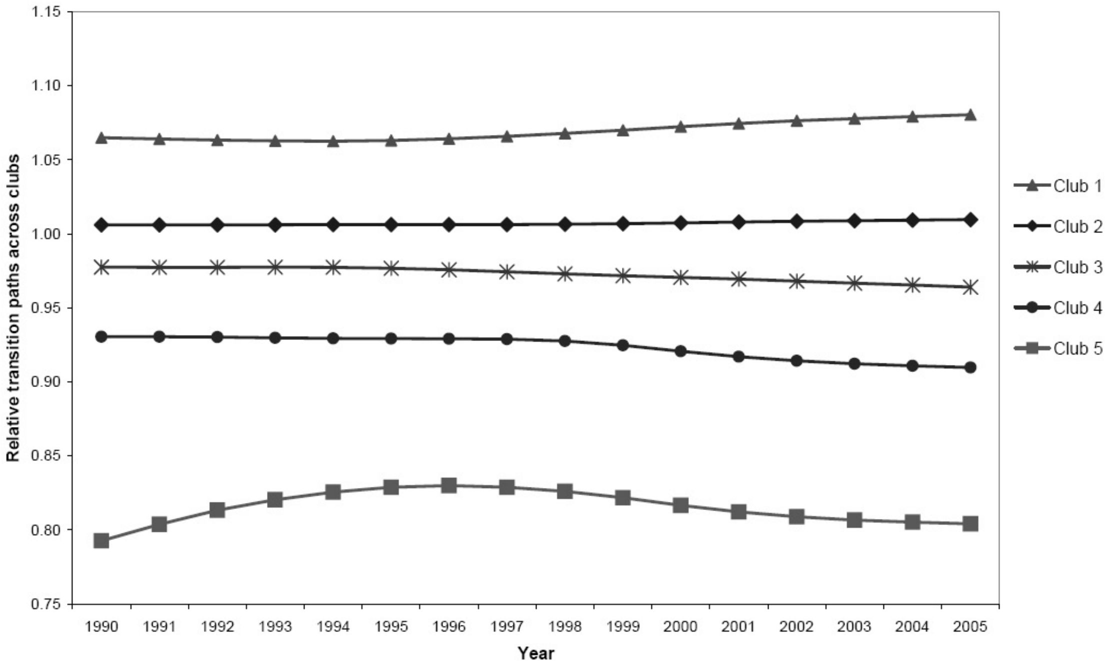

Figure 2: Transition paths

3. Factors conditioning club membership

3.1. Theoretical considerations and data

According to the club convergence hypothesis, economies that exhibit identical structural characteristics only converge with one another if they face the same initial conditions (Galor, 1996). In this section, we discuss the main factors mentioned by growth literature as potentially responsible for the formation of convergence clubs. Specifically, we focus on the initial conditions (at the starting point in 1990) that are crucial in determining the growth path of an economy, at the same time considering important structural characteristics of an economy in order to identify the initial conditions properly. Furthermore, we discuss indicators to measure these factors, as they will be employed in the ensuing subsection in order to empirically assess whether the theory can actually explain the convergence patterns observed among European regions. Table 2 provides the definition of the variables and the corresponding sources. For descriptive statistics, see Appendix D.

Theoretical contributions to growth theory identify a number of initial factors which may be decisive in determining an economy's long-run steady state path.[6] In the neoclassical framework (Solow, 1956), heterogeneity in factor endowments can explain the emergence of multiple steady state equilibria. In particular, if savings arise only out of wages, the initial level of the capital-labor ratio can determine which steady state an economy approaches (Galor, 1996; Deardorff, 2001). In order to control for differences in factor endowments across regions, we employ a labor force variable and use investment data to measure the capital stock of a region. Moreover, we use the capital share as a proxy

[6]See Galor (1996) for a comprehensive overview of theoretical models explaining convergence clubs.

for differences in factor intensities in order to reflect the relative importance of factors in production across regions.

Azariadis and Drazen (1990) augment the neoclassical growth model by incorporating threshold externalities in the accumulation of human capital which can induce multiple balanced growth paths as stationary equilibria. Specifically, initial conditions with respect to human capital accumulation may determine an economy's growth path. This is due to increasing social returns to scale that become particularly pronounced when the stock of knowledge attains critical mass values. In particular, the authors argue that rapid growth can only occur with a relatively overqualified labor force, that is, a high level of human investment relative to per capita income. In order to test this presumption, we use the educational attainment of the working-age population as a proxy for human capital[7] as well as GVA per worker as a measure for per capita income.

To identify the net impact of initial factors on the formation of convergence clubs, we consider indicators that control for an economy's structural characteristics. One particularly relevant and often cited prerequisite for a common steady state growth path of economies is similar production technology (e.g., Galor, 1996). In controlling for differences in production technologies across regions, we employ the share of high-tech production in total service and manufacturing production, relying on the OECD classification of technology- and knowledge-intensive sectors (see also Mora, 2008). In addition, we account for the industrial structure of a region by considering GVA in the service sector as a share of total GVA.

Quah (1996b) points to the importance of informational externalities for explaining the appearance of convergence clubs. These externalities may occur either at the state or at the neighborhood level, as information is likely to flow more easily across regions which belong to the same state or share a border. Hence, geographical location may determine the convergence club a region will join. Indeed, as already discussed in section 2.3 (see also figure 1), European regions belonging to the same country seem to form common convergence clubs. Also, as reflected by the value of the Moran's I statistic (i.e., 0.5: see section 2.3), neighboring regions tend to cluster together, indicating that physical location and geographical spillovers are relevant to the convergence process among European regions. In order to capture this form of externality we employ two different indicators. First, we use country dummies to control for country membership. Second, we consider the output per capita of neighboring regions to control for geographical spillovers. The idea is that the economic activity of bordering regions should influence a given region's economy and therefore have an impact on its convergence process. More specifically, we use the spatial lag of per capita income and apply a contiguity weighting matrix (W) of

[7] Unfortunately, data on educational attainment was not available at the regional level before 1995. However, as we can presume that the number of people with higher education does not vary significantly within a region over a five-year period, we use the respective 1995 data as a proxy for the starting point. The low variation implied in the time dimension of this variable is reflected by its development from 1995 to 1999. Over that five-year period, within-region variability amounts to 0.01, while cross-section variability is 0.05.

Table 2: Variables and sources

Variable	Definition	Source
Initial conditions		
Labor force	Active population as a share of total population: 1990	Cambridge Econometrics Database (CED)
Capital stock per capita	Perpetual inventory method assuming a depreciation rate of 10% (e.g., Keller, 2001) for investment data from 1980-1990, divided by the number of workers, in logs: 1990	own calculations, CED
Capital share	GVA minus compensation to employees, divided by nominal value added: 1990	CED
Human capital	Population with higher education (ISCED 5 and 6) as a percentage share of population older than 14: 1995	Labor Force Survey
Income per capita	GVA divided by number of workers, constant prices, in logs: 1990	CED
Structural characteristics		
High-tech production	GVA in high-tech manufacturing and services divided by GVA in total manufacturing and services: 1990, High-tech manufacturing sectors refer to Fuels, chemicals, rubber and plastic products and Electronics, High-tech service sectors refer to Transport and Communications and Financial services	CED
Services	GVA in the service sector as a share of total GVA: 1990	CED
Population growth	Average growth rate of total population between 1980 and 1990	CED
Country membership	Dummy variable for regions belonging to the same country	own calculations
W Income per capita	W multiplied by income per capita as defined above, where W refers to a row-standardized contiguity weighting matrix of order one: 1990	own calculation, CED
Agglomeration	Population density (area in square km): 1990	CED

order one, that is, regions sharing a border are defined as neighbors.[8]

Barro and Sala-i-Martin (1991) also argue that convergence is more likely among regions within a country than among regions situated in different countries because institutional frameworks, regulatory systems, consumer tastes, and technologies are more similar within a country than between different countries. As we consider country dummies, we are able to account for these country-specific factors as well.

An important growth determinant in neoclassical models is the rate of population growth, which we also include in our set of explanatory variables (Mora, 2008). Finally, as

[8]Note that an island's neighbor is the region nearest to that island in terms of geographical distance.

the geographical agglomeration of economic activities may also reinforce economic growth, we add population density to our set of explanatory variables to control for agglomerated regions (e.g., Corrado et al., 2005; Martin and Ottaviano, 2001).

3.2. Results from an ordered probit model

In order to explain the formation of clubs across European regions, we employ an ordered regression model as first introduced by McKelvey and Zavoina (1975). The variable to be explained, which is denoted by c, represents the club to which a region belongs. As the fifth club consists of only three regions, we pool clubs 4 and 5 into a single club, meaning that c can take on values from 1 to 4. This variable can be classified as an ordinal variable since the observed clubs can be ranked according to the steady state per capita income levels of regions in the respective club (see table 1). However, the differences between steady state levels across clubs are not known. For example, regions belonging to the first club converge to a higher steady state income level than regions belonging to the remaining clubs. Assuming that membership in a certain club is related to a continuous, latent variable y_i^* that indicates a region's individual steady state income level, the model can be written as

$$y_i^* = X_i\beta + \epsilon_i \tag{10}$$

where X_i contains the explanatory variables (in the initial period) listed in table 2 as well as a constant term, with $i = 1, ..., 206$ indicating the region. The column vector β includes the structural coefficients. As the dependent variable y_i^* is unobserved, the model cannot be estimated with OLS. Instead, maximum likelihood (ML) techniques are applied to compute the probabilities of observing values of c given X (ordered regression model). In order to use ML, the distribution of the error term ϵ_i has to be specified. As it is convenient, we assume the errors to be normally distributed with a mean zero and a variance of one, meaning that the resulting ordered regression model can be referred to as a probit model. Since the latter is non-linear in its probability outcomes, the impact of a variable on the outcomes can be interpreted in various ways. In order to explore the effect of a single variable on the probability of membership in a specific club, we follow the literature and report marginal effects on the probabilities of each variable evaluated at its mean and at the mean of all other explanatory variables. Furthermore, as we are particularly interested in the influence of initial conditions on the formation of convergence clubs, we display the entire probability curve for each of the initial conditioning variables (given that they are significant) by holding the remaining variables constant. As a result, we can observe the probabilities of belonging to a certain club depending on the level of the corresponding variable.[9]

In table 3, we report marginal effects for each outcome of the club variable c. At the bottom of the table, we display the number of regions belonging to a particular club

[9] For an overview of ordered probit models, see e.g., Greene (2000) and Long (1997). Estimation was performed using the command oprobit in Stata.

Table 3: Marginal Effects on Probabilities

Variable	Club 1	Club 2	Club 3	Club 4 & 5
Initial conditions				
Labor force	0.502**	1.138**	-1.524***	-0.111*
	(0.213)	(0.449)	(0.526)	(0.068)
Capital stock per capita	0.030	0.069	-0.093	-0.007
	(0.032)	(0.074)	(0.098)	(0.008)
Capital share	0.305**	0.690**	-0.928***	-0.067
	(0.137)	(0.271)	(0.325)	(0.042)
Human capital	0.005**	0.012**	-0.016**	-0.001
	(0.003)	(0.006)	(0.007)	(0.001)
Income per capita	0.277***	0.628***	-0.844***	-0.061*
	(0.105)	(0.214)	(0.239)	(0.036)
Structural characteristics				
Services	0.409***	0.926***	-1.244***	-0.090*
	(0.158)	(0.336)	(0.380)	(0.053)
High-tech production	0.447**	1.012**	-1.361**	-0.098
	(0.217)	(0.450)	(0.552)	(0.064)
Population growth	0.763	1.727	-2.322	-0.168
	(4.198)	(9.498)	(12.758)	(0.931)
Agglomeration	0.009	0.020	-0.027	-0.002
	(0.016)	(0.036)	(0.049)	(0.004)
W income per capita	-0.144*	-0.325**	0.437**	0.032
	(0.074)	(0.163)	(0.120)	(0.022)
Number of regions	33	111	40	22
Country dummies	yes	yes	yes	yes

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Notes: Marginal effects are computed at the mean of all variables as an approximation of average marginal effects. Country dummies were included but are not reported for the sake of brevity. Standard errors are reported in parentheses. A definition of the variables and their sources are provided in table 2.

and indicate the inclusion of country dummies (not reported).[10] The individual partial derivatives show the change in the probability of belonging to a specific club given a small change in the explanatory variables. In this way, the probability of membership in the first three clubs is explained quite well by the chosen variables, while this does not hold for the last club(s), which include the 22 least developed regions. This might be due to the fact that the sample size is smaller, meaning that the effects which are significant for the first three clubs are only significant at the 15% level. However, a clear picture arises from the first three columns. Apart from the capital stock variable, all of the initial conditions play a significant role in explaining a region's membership in a specific club. In particular, a small positive change in these variables raises the probability of belonging to a high-income club (club 1 or club 2), while it decreases the probability of belonging to a lower-income club such as club 3.[11] We can thus conclude that the initial conditions explored by growth theory appear to be relevant in explaining club formation among

[10]Note that we only include significant country dummies, that is, dummies for the UK, Germany, Spain and the Netherlands. They were selected according to a drop-down procedure in which we first estimated the model including all dummies and then dropped the insignificant ones (lowest t-value) one at a time.

[11]Note that the sums of the estimated partial derivatives are equal to zero across the four clubs because the sums of the probabilities must always equal one.

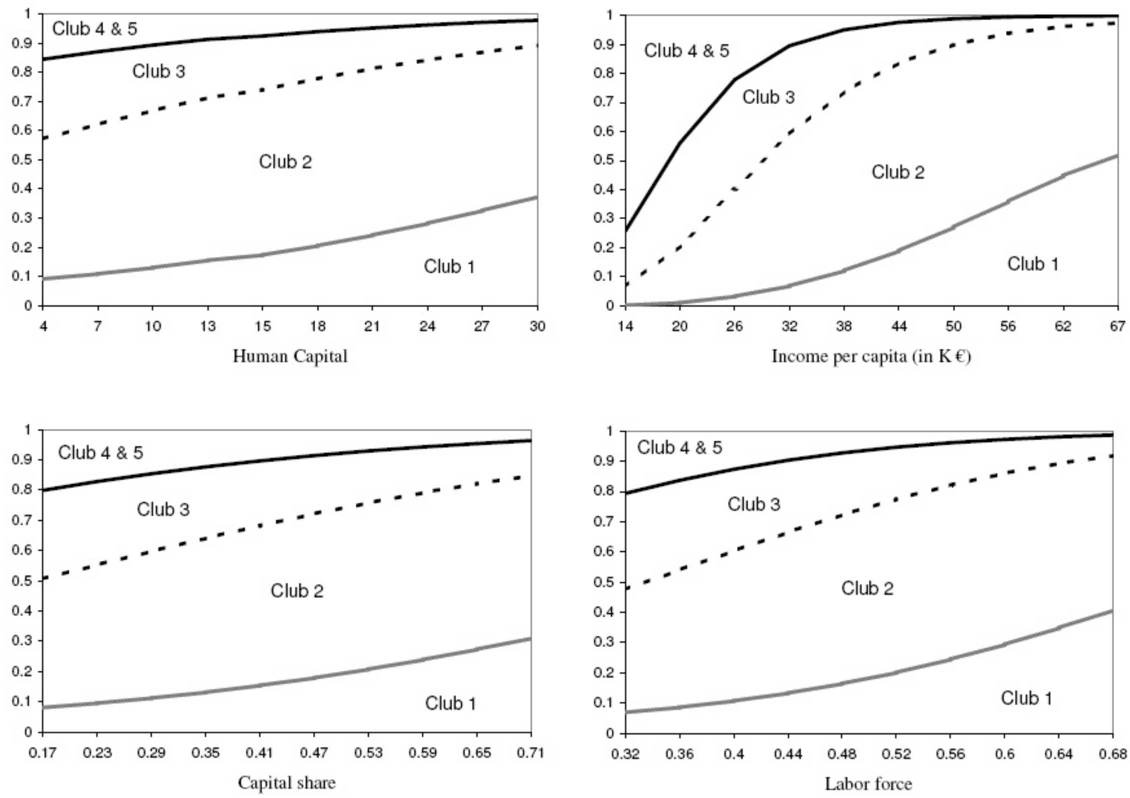

Figure 3: Cumulative probability for initial conditions

European NUTS2 regions.

Concerning the partial derivatives with respect to structural characteristics, the same broad picture emerges. Apart from agglomeration and population growth, which have insignificant effects, both technology variables have the expected positive influence on the probability of belonging to a high-income club and a negative impact on the probability of ending up in a low-income club (clubs 3 and 4). Interestingly, the per capita income of neighboring regions seems to have a counterintuitive effect on club membership. In particular, an increase in a neighboring region's income tends to reduce a region's probability of belonging to club 1 or 2. Although this conflicts with our expectations, a visual inspection of the map in figure 1 supports the estimation outcome, as it can be seen that regions belonging to club 1 (mostly metropolitan areas) and club 2 are mainly surrounded by regions belonging to a club experiencing lower per capita income. This might be the result of backwash effects (Myrdal, 1957), that is, regions from high-income clubs draw resources such as labor or capital away from their neighbors, which consequently end up with lower per capita income.

Finally, we explore how the probability of being a high-income (low-income) region changes when we vary the level of initial conditions. Specifically, we consider each of the significant variables, that is, human capital, income per capita, capital share and the labor force, holding the remaining variables constant. In figure 3, we plot the probabilities that the outcome is less than or equal to c over the range of values for the respective variable (i.e., the probability of at least belonging to club c). For example, the lower line in the graphs shows the probability of belonging to club 1 when the value of the respective variable is altered. In general, all four graphs show the same pattern. The first graph reveals that regions with a high initial endowment of human capital, that is, 30% highly educated inhabitants, experience a 33% higher probability (from 0.6 to 0.8) of belonging to a high-income club (club 1 or 2) than regions with a low initial endowment of human capital (4%). The effect of initial conditions on the probability of converging to club 1 or 2 is even more pronounced when it comes to per capita income. The probability that regions which exhibited low income in the initial period, say $14,000$ euros, will at least belong to the second income club is only 0.08, while regions with high per capita incomes, such as $67,000$ euros, show a probability of 0.98 of converging to a high-income club. In summary, we can confirm that the initial conditions put forward by growth theory do in fact determine the path of convergence among European regions' per capita incomes.

4. Conclusion

In recent years there has been increasing interest in empirically investigating the club convergence hypothesis in general and in identifying convergence clubs among economies in particular. One strand of this literature focuses on the endogenous determination of groups of economies that converge to the same steady state level, that is, by leaving factors unspecified that might be responsible for the formation of convergence clubs. Such an approach overcomes the drawback that the resulting cluster outcome is predetermined, as would be the case if a priori grouping criteria were chosen. However, the caveat associated with studies that endogenously identify convergence clubs is that they cannot confirm whether the latter are attributable to the *club convergence* hypothesis or whether *conditional convergence* applies.

In this paper, we have suggested a two-step procedure to empirically test the *conditional convergence* hypothesis for 206 Western European NUTS2 regions over the 1990-2005 period. First, we applied the log t test (Phillips and Sul, 2007) in order to endogenously identify potential convergence clubs and, in a second step, we analyzed which factors have an impact on the probability of belonging to a certain club. In particular, we tested whether club membership depends on a region's starting conditions, such as the initial level of human capital and per capita income as suggested by Azariadis and Drazen (1990), or rather on a region's structural characteristics only. This differentiation allowed us to disentangle *club convergence* from *conditional convergence*. Additionally, we have accounted for the role of space in our analysis by applying Getis' filter (1995) to remove the spatial component inherent in regional income data and by studying the role of neighboring regions' per capita incomes for a given region's club membership.

Our main findings can be summarized as follows: The results of the log t test point to the existence of five convergence clubs in terms of per capita income across European NUTS2 regions. Moreover, estimates from an ordered probit model reveal that initial conditions such as a region's initial level of human capital and per capita income can indeed explain to which club a region will belong, at the same time controlling for its structural characteristics. Therefore, we can conclude that the observed convergence clubs can partly be explained by the *club convergence* hypothesis.

Finally, we would like to point to some possible avenues for future research on club convergence. The probably most challenging issue is related to the question which starting point the researcher should ideally choose when analyzing the relevance of initial conditions for the convergence process of an economy (e.g., Islam, 2003). In this study the starting point was chosen according to the earliest available data. Of course, this is arbitrary and it would be desirable to somehow endogenously identify the point in time where initial conditions might determine an economy's growth path. To our knowledge, this topic has not been addressed in the literature so far. A necessity related to this challenge is the extension of existing data sets to longer time periods, especially at the regional level. Moreover, extending the analysis to Eastern European regions would allow us to draw conclusions on the progress of integration within the enlarged European Union. Unfortunately, due to a substantial change in accounting conventions in the former centrally planned economies, no reliable data before 1995 is available. This complicates the analysis as the power of the suggested convergence test is unsatisfactory for panels with a time dimension around ten. Hence, a different approach would have to be considered to analyze the convergence process across regions of the enlarged European Union. This seems to be an interesting field for future research.

Acknowledgments. The authors gratefully acknowledge Grant No. P19025-G11 provided by the Austrian Science Fund (FWF). They would also like to thank Manfred M. Fischer and the participants in the 3rd World Conference of the Spatial Econometrics Association in 2009 for useful discussions and suggestions.

Appendix A. Sample

Our sample includes 206 NUTS2 regions in 17 countries, including Austria (nine regions), Belgium (11 regions), Denmark (one region), Finland (five regions), France (22 regions), Western Germany (30 regions), Greece (13 regions), Italy (20 regions), Ireland (two regions), Luxembourg (one region), the Netherlands (12 regions), Norway (seven regions), Portugal (five regions), Spain (16 regions), Sweden (eight regions), Switzerland (seven regions) and the UK (37 regions). The NUTS2 codes for each region are reported in parenthesis.

Austria Burgenland (AT11); Niederösterreich (AT12); Wien (AT13); Kärnten (AT21); Steiermark (AT22); Oberösterreich (AT31); Salzburg (AT32); Tirol (AT33); Vorarlberg (AT34)

Belgium Rêgion de Bruxelles-Capitale/Brussels Hoofdstedelijk Gewest (BE10); Prov. Antwerpen (BE21); Prov. Limburg (BE22); Prov. Oost-Vlaanderen (BE23); Prov. Vlaams-Brabant (BE24); Prov. West-Vlaanderen (BE25); Prov. Brabant Wallon (BE31); Prov. Hainaut (BE32); Prov. Liège (BE33); Prov. Luxembourg (BE34); Prov. Namur (BE35)

Denmark Danmark (DK00)

Finland Itä-Suomi (FI13); Etelä-Suomi (FI18); Länsi-Suomi (FI19); Pohjois-Suomi (FI1A); Åland (FI20)

France Île-de-France (FR10); Champagne-Ardenne (FR21); Picardie (FR22); Haute-Normandie (FR23); Centre (FR24); Basse-Normandie (FR25); Bourgogne (FR26); Nord - Pas-de-Calais (FR30); Lorraine (FR41); Alsace (FR42); Franche-Comté (FR43); Pays de la Loire (FR51); Bretagne (FR52); Poitou-Charentes (FR53); Aquitaine (FR61); Midi-Pyrénées (FR62); Limousin (FR63); Rhône-Alpes (FR71); Auvergne (FR72); Languedoc-Roussillon (FR81); Provence-Alpes-Côte d'Azur (FR82); Corse (FR83)

Germany Stuttgart (DE11); Karlsruhe (DE12); Freiburg (DE13); Tübingen (DE14); Oberbayern (DE21); Niederbayern (DE22); Oberpfalz (DE23); Oberfranken (DE24); Mittelfranken (DE25); Unterfranken (DE26); Schwaben (DE27); Bremen (DE50); Hamburg (DE60); Darmstadt (DE71); Gießen (DE72); Kassel (DE73); Braunschweig (DE91); Hannover (DE94); Lüneburg (DE93); Weser-Ems (DE94); Düsseldorf (DEA1); Köln (DEA2); Münster (DEA3); Detmold (DEA4); Arnsberg (DEA5); Koblenz (DEB1); Trier (DEB2); Rheinhessen-Pfalz (DEB3); Saarland (DEC0); Schleswig-Holstein (DEF0)

Greece Anatoliki Makedonia, Thraki (GR11); Kentriki Makedonia (GR12); Dytiki Makedonia (GR13); Thessalia (GR14); Ipeiros (GR21); Ionia Nisia (GR22); Dytiki Ellada (GR23); Sterea Ellada (GR24); Peloponnisos (GR25); Attiki (GR30); Voreio Aigaio (GR41); Notio Aigaio (GR42); Kriti (GR43)

Italy Provincia Autonoma Bolzano/Bozen & Provincia Autonoma Trento (IT31); Piemonte (ITC1); Valle d'Aosta/Vallée d'Aoste (ITC2); Liguria (ITC3); Lombardia (ITC4); Veneto (ITD3); Friuli-Venezia Giulia (ITD4); Emilia-Romagna (ITD5); Toscana (ITE1); Umbria (ITE2); Marche (ITE3); Lazio (ITE4); Abruzzo (ITF1); Molise (ITF2); Campania (ITF3); Puglia (ITF4); Basilicata (ITF5); Calabria (ITF6); Sicilia (ITG1); Sardegna (ITG2)

Ireland Border, Midland and Western (IE01); Southern and Eastern (IE02)

Luxembourg Luxembourg (Grand-Duché) (LU00)

Netherlands Groningen (NL11); Friesland (NL12); Drenthe (NL13); Overijssel (NL21); Gelderland (NL22); Flevoland (NL23); Utrecht (NL31); Noord-Holland (NL32); Zuid-Holland (NL33); Zeeland (NL34); Noord-Brabant (NL41); Limburg (NL42)

Norway Oslo og Akershus (NO01); Hedmark og Oppland (NO02); Sør-Østlandet (NO03); Agder og Rogaland (NO04); Vestlandet (NO05); Trøndelag (NO06); Nord-Norge (NO07)

Portugal Norte (PT11); Algarve (PT15); Centro (PT16); Lisboa (PT17); Alentejo (PT18)

Spain Galicia (ES11); Principado de Asturias (ES12); Cantabria (ES13); País Vasco (ES21); Comunidad Foral de Navarra (ES22); La Rioja (ES23); Aragón (ES24);

Comunidad de Madrid (ES30); Castilla y León (ES41); Castilla-La Mancha (ES42); Extremadura (ES43); Cataluña (ES51); Comunidad Valenciana (ES52); Illes Balears (ES53); Andalucía (ES61); Región de Murcia (ES62)

Sweden Stockholm (SE01); Östra Mellansverige (SE02); Sydsverige (SE04); Norra Mellansverige (SE06); Mellersta Norrland (SE07); Övre Norrland (SE08); Småland med öarna (SE09); Västsverige (SE0A)

Switzerland Région lémanique (CH01); Espace Mittelland (CH02); Nordwestschweiz (CH03); Zürich (CH04); Ostschweiz (CH05); Zentralschweiz (CH06); Ticino (CH07)

United Kingdom Tees Valley and Durham (UKC1); Northumberland and Tyne and Wear (UKC2); Cumbria (UKD1); Cheshire (UKD2); Greater Manchester (UKD3); Lancashire (UKD4); Merseyside (UKD5); East Riding and North Lincolnshire (UKE1); North Yorkshire (UKE2); South Yorkshire (UKE3); West Yorkshire (UKE4); Derbyshire and Nottinghamshire (UKF1); Leicestershire, Rutland and Northamptonshire (UKF2); Lincolnshire (UKF3); Herefordshire, Worcestershire and Warwickshire (UKG1); Shropshire and Staffordshire (UKG2); West Midlands (UKG3); East Anglia (UKH1); Bedfordshire and Hertfordshire (UKH2); Essex (UKH3); Inner London (UKI1); Outer London (UKI2); Berkshire, Buckinghamshire and Oxfordshire (UKJ1); Surrey, East and West Sussex (UKJ2); Hampshire and Isle of Wight (UKJ3); Kent (UKJ4); Gloucestershire, Wiltshire and North Somerset (UKK1); Dorset and Somerset (UKK2); Cornwall and Isles of Scilly (UKK3); Devon (UKK4); West Wales and the Valleys (UKL1); East Wales (UKL2); North Eastern Scotland (UKM1); Eastern Scotland (UKM2); South Western Scotland (UKM3); Highlands and Islands (UKM4); Northern Ireland (UKN0)

Appendix B. Convergence club identification

Appendix B.1. Clustering algorithm

If the null hypothesis of overall convergence is rejected, club convergence can be identified via the clustering algorithm presented by Phillips and Sul (2007). This algorithm consists of the following steps:

Step 1: Cross-section ordering by final observation
Convergence, also within clubs, as $T \to \infty$ is usually most evident in the final time series observations. The units of the cross-section should be sorted in descending order on the basis of the last period in the time series dimension of the panel. In the case of significant volatility in X_{it}, sorting can be based on the time series average over the last 1/2 or 1/3 periods of the time dimension.

Step 2: Formation of core group of k^* regions
Take the first k units (with $2 \leq k < N$) from the panel and run the log t regression. If $t_{\hat{b}}$ for these k units is larger than -1.65, add further units one by one, calculating $t_{\hat{b}}$ for the

k selected units each time. Continue as long as $t_{\hat{b}}$ increases and is larger than -1.65 (at the 5% significance level). After obtaining a smaller value for $t_{\hat{b}}$, conclude that the core group with $k^* = k - 1$ members of a club has been formed. If $t_{\hat{b}} > -1.65$ does not hold for the first two units, drop the first unit and run the log t regression for the second and third units. Continue until a pair of units is found where $t_{\hat{b}} > -1.65$. If there are no such units in the entire sample, conclude that there are no convergence clubs in the panel.

Step 3: Sieve the data for new club members

After identifying the core group of a club, conduct a test for the club membership of other units in the panel. Add one of the remaining units at a time to the k^* members of the core group and run the log t regression. Repeat for all units outside of the core group. Select units where $t_{\hat{b}} > c$, with c being a critical value ($c \geq 0$), and add them to the core group. Run the log t test for the entire group. If $t_{\hat{b}} > -1.65$, conclude that this group constitutes a convergence club. Otherwise, increase the critical value for the club membership selection, form a new group consisting of the core group and all the units where $t_{\hat{b}}$ is larger than the increased critical value, and run the log t regression. Repeat until $t_{\hat{b}} > -1.65$ for the entire group. Then conclude that those units form a convergence club. If there are no units apart from the core group that result in $t_{\hat{b}} > -1.65$, conclude that the convergence club consists only of the core group.

Step 4: Recursive and stopping rule

Form a second group from all the units outside of the convergence club, that is, where $t_{\hat{b}} < c$. Run the log t test for the entire group to check whether $t_{\hat{b}} > -1.65$ and the group converges. If not, repeat Steps 1-3 on this group to determine whether the panel includes a smaller subgroup that forms a convergence club. If there is no k in Step 2 for which $t_b > -1.65$, conclude that the remaining units diverge.

Appendix B.2. Test for merging

Phillips and Sul (2009) suggest the following test for merging between the groups formed according to the clustering algorithm described in the Appendix B.1: Take the first and the second group and run the log t test: if the t-statistic is larger than -1.65 (5% significance level), assume that both groups form a club together. Repeat the test after adding the next group and continue until the t-statistic indicates that the convergence hypothesis is rejected. Conclude that all of the groups except the last one converge, and start the test again beginning with the group for which the convergence hypothesis was rejected.

Appendix C. Identified convergence clubs

Club 1 AT13, AT34, BE10, BE21, BE24, BE31, CH01, CH02, CH03, CH04, CH05, CH06, CH07, DE21, DE60, DE71, FR10, FR82, GR30, GR42, IE02, LU00, NL11, NO01, NO04, NO05, NO06, SE01, SE04, UKH2, UKI1, UKJ1, UKK1

Club 2 AT11, AT12, AT21, AT22, AT31, AT32, AT33, BE22, BE23, BE25, BE32, BE33, BE34, BE35, DE11, DE12, DE13, DE14, DE22, DE23, DE24, DE25, DE26, DE27, DE50, DE72, DE73, DE91, DEA1, DEA2, DEA5, DEB3, DEC0, DEF0, DK00, FI18, FI19, FI20, FR21, FR22, FR23, FR24, FR25, FR26, FR30, FR41, FR42, FR43, FR51, FR52, FR53, FR61, FR62, FR63, FR71, FR72, FR81, FR83, GR22, GR24, GR43, IE01, IT31, ITC1, ITC2, ITC3, ITC4, ITD3, ITD4, ITD5, ITE1, ITE4, ITF4, ITF6, ITG1, NL31, NL32, NL33, NL34, NL41, NL42, NO02, NO03, PT17, SE02, SE06, SE07, SE08, SE09, SE0A, UKC2, UKD2, UKD3, UKE2, UKE4, UKF1, UKF2, UKG1, UKG3, UKH1, UKH3, UKI2, UKJ2, UKJ3, UKJ4, UKK2, UKK3, UKL2, UKM1, UKM2, UKM3

Club 3 DE92, DE93, DE94, DEA3, DEA4, DEB1, DEB2, ES11, ES12, ES21, ES30, ES43, ES51, ES61, FI13, FI1A, ITE2, ITE3, ITF1, ITF2, ITF3, ITF5, ITG2, NL12, NL13, NL21, NL22, NO07, PT15, PT18, UKC1, UKD4, UKD5, UKE1, UKE3, UKF3, UKG2, UKK4, UKL1, UKN0

Club 4 ES13, ES22, ES23, ES24, ES41, ES42, ES52, ES53, ES62, GR11, GR12, GR13, GR14, GR21, GR25, GR41, NL23, UKD1, UKM4

Club 5 GR23, PT11, PT16

Appendix D. Descriptive Statistics

Table D.4: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
Initial conditions					
Labor force	0.467	0.068	0.315	0.697	206
Capital stock per capita*	72.551	24.114	22.310	182.169	206
Capital share	0.434	0.096	0.164	0.744	206
Human capital	12.776	4.766	3.371	31.057	206
Income per capita*	39.302	9.246	13.377	67.468	206
Structural characteristics					
Services	0.666	0.076	0.452	0.872	206
High-tech production	0.180	0.051	0.078	0.480	206
Population growth	0.001	0.002	-0.003	0.014	206
Agglomeration	0.350	0.838	0.003	8.231	206
W income per capita*	39.104	7.710	16.941	58.370	206

* in thousand euros

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