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Don J. Webber[1], Min Hua Jen[2] and Eoin O'Leary[3]

[1] *Department of Accounting, Economics and Finance, University of the West of England, Bristol, UK*
[2] *Dr Foster Unit, Imperial University, London, UK*
[3] *Institute for Business Development and Competitiveness, School of Economics, University College Cork, Ireland*

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[1] *Department of Accounting, Economics and Finance, University of the West of England, Bristol, UK*
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This paper examines productivity dynamics at different spatial scales across European countries. Application of non-parametric simultaneous estimation techniques to a hierarchical dataset permits us to consider explicitly the extent to which the national-level is important for understanding regional-level productivity variation. The results show considerable national and regional level productivity variation which is not constant and evolves over time. There is divergence at all spatial scales and groups of regions that follow different growth trajectories with group membership not being confined by national borders. The results imply that policymakers need to take cognizance of the multi-layered economic geographies in which they are located. There are also group dynamics that challenge the dominance of the national economic positions and should be considered when shaping policy.

Keywords: Multi-level modelling; Regional productivity; Groups

JEL Nos: R11; O47

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Address for correspondence: Don J Webber, Department of Accounting, Economics and Finance, University of the West of England, Bristol, BS16 1QY, UK. Email: Don.Webber@uwe.ac.uk.

1. Introduction

The debate on the nature and causes of regional productivity change continues to evolve. Since the 1980s, neoclassical and endogenous growth theory and new economic geography have stimulated a vast array of empirical work on regional convergence both within and between countries (Barro and Sala-i-Martin, 1991; Bernard and Dulauf, 1995; Quah, 1996a). More recently, evolutionary economic geography has emerged with its emphasis on path-dependence and regional lock-in (Martin and Sunley, 2006). From a policy perspective, the discussion has switched from targeting measures at poorer regions thereby bringing about regional convergence to attempting to help regions fulfil their growth potential. Baumol's (1986) notion of a convergence club, which has been extended by Durlauf and Johnson (1995) and Galor (1996), is where a group of economies have initial conditions that are near enough to converge towards an identical long-term equilibrium. This paper proposes a slightly different type of convergence club, and to distinguish these from the more traditional meaning of club we will refer to them as groups: here a group is a group of regions that appear to follow a similar productivity trajectory over time, which includes coinciding down- and upturns over time, and is not necessarily dependent on initial conditions.

Recent banking and sovereign debt crises have raised questions about the survival of the EU and the Euro. The resulting debate on a federal or a two/multi-speed Europe serves as a reminder that short-term shocks and longer-term variations in fundamental factors acting at higher spatial levels should not be ignored in considerations of regional growth. Therefore a region's growth may not only be influenced by resources and institutions operating within and around it, but also by changes in these factors at the national level, which simultaneously affect regional change.

We follow the idea that regional change is not only affected by factors working within and between regions, it may also be influenced by changes occurring at a higher spatial level, especially within hierarchical settings. Adopting this perspective leads to the recognition that it is important to investigate the extent to which national-level changes simultaneously affect regional change. This paper introduces multi-level time-series-cross-section regression and a group-based trajectory approach to the regional productivity literature in an effort to identify groupings and hierarchical behaviour across European countries and regions. These are powerful and as yet underused techniques in the regional growth literature. These techniques are applied to Cambridge Econometrics data with observations for 29 NUTS0, 90 NUTS1 and 233 NUTS2 regions between 1980 and 2007.

The paper has four key objectives: first, to identify whether regional productivity evolution is homogenous within country borders; second, to identify whether the importance of country affiliation has diminished over time; third, to ascertain whether regional growth patterns are randomly distributed or whether regions are unambiguously grouped together; and fourth, to identify whether regions form groups countries and whether these groups are confined by national borders.

This paper has the following structure. The next section reviews the relevant literature. Section 3 describes the hierarchical dataset and provides a broad brush picture of productivity patterns across Europe. Section 4 details two methods: one for analysing simultaneously productivity evolutions of multiple nested data and one for classifying dynamic groups. Section 5 summarises and discusses the results, and Section 6 draws conclusions.

2. The importance of national borders for regional groups

From a theoretical perspective it is implicitly assumed that the engines of growth that characterize neoclassical and new growth theory may operate at different spatial levels. The neoclassical emphasis on capital accumulation and the new growth theory's emphasis on endogenizing broad capital, human capital or innovation may operate at either national or regional levels. As a result, a substantial amount of empirical research has been conducted since the late 1980s to investigate the roles of these factors at national (see Islam, 2003) and regional levels (Neven and Gouymte, 1995; Sala-i-Martin, 1996; Martin and Sunley, 1998). The new economic geography perspective, which highlights specialization and agglomeration effects (Krugman, 1991), has emphasized the need for greater analysis at the regional level. More recently, discussions of path-dependence and regional lock-in (Martin and Sunley, 2006) are suggestive of a further progression of the analysis into a region's history and evolution. Notwithstanding these developments, it is important for regional researchers not to overlook the potential importance of national changes for regional growth.

The vast body of empirical research that has emerged on the extent of European national and regional convergence has yielded two key stylized facts. First, although national productivity convergence has been present, it has been slow.[1] Mankiw *et al*. (1992) point out that *if* countries have *permanent* differences in their production functions (i.e. different initial period levels of technological development) then the technology in a production function (A) would enter as part of the error term and would be positively correlated with initial per capita income [i.e. $\text{error}_{it}=f(A)$], hence the use of the initial or 1-period lagged output as the convergence parameter. However, this is a big *if*, especially if technology varies over time and across sectors, which is likely to be the case especially at small spatial scales. Second, the remarkably slow rate of regional productivity convergence is attributable to reductions in disparities between member states (Gardiner *et al*., 2004).

One of the main contributions of this paper is to introduce multi-level analysis, whereby variations at national and regional levels are simultaneously analysed. Some studies of the extent of convergence or divergence across European regions have controlled for national effects, but this has typically involved introducing into the regional models country-level fixed or random effects that are assumed to capture unobserved heterogeneity that is constant over time. Through application of a multi-level modelling perspective it is possible to relax this strict and most probably unrealistic assumption and instead to simultaneously model the regional- and national-level variation over time.

It has long been recognized that administrative regions are not an ideal measure of functional regions (Magrini, 1999). This argument not only applies to regions but also to nations as some city regions, such as Luxembourg, might extend across national borders (Chilla, 2011). Despite this drawback, studies of regional growth inevitably employ official data on administrative regions, as these relate to categories for which the required data are collected. Furthermore, from a policy perspective, there are good reasons to analyse official data as these are used to direct policy. Therefore, rather than selecting one spatial category, as is the practice in most

[1] Following the work of Quah (1996b), a substantial body of research has been conducted on the existence of convergence clubs. More recently, Corrado *et al*. (2005) have used an inductive approach to identify regional groups at the NUTS1 level in Europe.

studies, this study employs country level (or NUTS0) data as well as NUTS1 and NUTS2 regional level data.

3. European national and regional productivity data: 1980 – 2007

The empirical analysis uses data corresponding to 29 European countries (i.e. NUTS0), 74 NUTS1 and 233 NUTS2 regions for the period 1980 to 2007. The data have been extracted from the Cambridge Econometrics database, which provides gross value added (GVA) at constant €2000 basic prices and purchasing power standards and labour input for European regions between 1980 and 2007. Labour input is measured as total hours worked, computed as employment multiplied by average weekly hours worked. Accordingly, labour productivity is measured as GVA per workhour.[2] The Cambridge Econometrics dataset draws data from REGIO, which is the official source of EU regional data (Eurostat, 2004), and uses smoothing techniques to account for missing data.[3] This data set allows us to maximise the length of time under scrutiny and it coincides with the end of a boom period. (We choose not to include the predicted observations in the dataset in our analysis that correspond to the period 2008 onwards). It should be noted that any data smoothing by Cambridge Econometrics will increase the probability of convergence and reduce the probability of obtaining non-convergence results.

Table 1 lists the countries (or NUTS0 regions) and the number of NUTS1 and 2 regions included in the sample. For the vast majority of regions data are available from 1980 to 2007. However, for the recent EU entrants and the regions of the former East Germany data are only available from 1990.[4] As a result an unbalanced panel of 29 NUTS0, 90 NUTS1 and 233 NUTS2 regions are being investigated. The dataset has a strict hierarchical structure in that productivity measures for NUTS2 regions are nested within NUTS1 regions, which in turn are nested into countries.

{Insert Table 1 about here}

A comparison of productivity values for 1980 and 2007 is shown on Figure 1 where each NUTS2 region is shown as a circle. If a circle lies on the 45° line then that region has not experienced any growth in productivity per worker-hour between 1980 and 2007. Two regions lie below this line – Agder og Rogaland in Norway and Sterea Ellada in Greece – which suggest a contraction in their labour productivity. Many NUTS2 regions are fairly close to the indicated regression line, indicating a similarity in productivity change performance across the range. There are also a number of very well performing regions.

{Insert Figure 1 here}

2 Gardner *et al*. (2004) argued for the superiority of hours worked as a measure of labour input in productivity analysis.
3 REGIO is incomplete, with full series not available for all EU countries.
4 We conducted a stability check to identify whether qualitatively identical results stand for 1990 onwards. This indeed was the case.

4. Multi-level regression and group-based trajectory analysis

This paper employs two main statistical approaches. We initially employ multi-level time-series-cross-section regression. This allows us to unequivocally consider the nested nature of the data and it permits the explicit identification of temporal changes in the variance of a particular regional level once analysis has considered simultaneously the variance at other levels; it is also possible to identify whether each level's variance co-varies with time. This statistical line of research is particularly pertinent for data that are nested and strictly hierarchical, as is the case with NUTS2, NUTS1 and NUTS0 regional data. This differs from extant research in this literature which applies fixed or random effects, which are assumed constant over time, to capture unobserved heterogeneity. The second statistical method applied here is a group-based trajectory analysis, which allows us to categorize regions into groups based on the similarity of productivity values over time. The investigation of these methods is also new to this literature.

Multi-level time-series-cross-section regression

Adopting a multi-level modelling approach permits the researcher to deal directly with the hierarchical structure of a data set. Application of this method to productivity data permits the simultaneous analysis of data variation at all levels; for instance, it could permit an analysis of NUTS1 regional data after account has been taken of the evolution and variance at the NUTS0 (country) level; in other words it allows for local analyses after account have been taken for global trends. This is important if the researcher is interested in variations in behaviour at different data levels.

Failing to take account of the data structure might lead to inaccurate and/or biased estimation results as it would necessarily require the assumption that each region is independent and identically distributed within the sample, which is unlikely to be case as a NUTS2 region may have more in common with other NUTS2 regions that are contiguous or from the same NUTS1 region; similar arguments are present when NUTS1 regions are nested within NUTS0 regions.

The simplest three-level model of productivity which can be applied to identify broad patterns of evolution and change can be specified as:

$$\begin{aligned} y_{ijkl} &= \beta_{0ijkl} \\ \beta_{0ijkl} &= \beta_0 + f_{0l} + v_{0kl} + u_{0jkl} + e_{0ijkl} \end{aligned} \tag{1}$$

and extended to include a time parameter, such that:

$$\begin{aligned} y_{ijkl} &= \beta_{0ijkl} + \beta_{1j} T_{ijkl} \\ \beta_{0ijkl} &= \beta_0 + f_{0l} + v_{0kl} + u_{0jkl} + e_{0ijkl} \\ \beta_{1ijkl} &= \beta_1 + f_{1l} + v_{1kl} + u_{1jkl} + e_{1ijkl} \end{aligned} \tag{2}$$

where y_{ijkl} is a measure of productivity for NUTS2 region *j* within NUTS1 region *k* within NUTS0 country *l* in year *i*. In (2) productivity is determined by the intercept, which effectively captures the initial global-mean productivity position and we would expect it to be statistically significant in empirical estimates due to path dependency, and time, T_{ijkl} . T has been centred around the year 1993 so that the fixed parameter, β_0, is an estimate of the global-mean productivity in 1993 year, and β_1 is the global-mean linear increase in NUTS2 regional productivity per annum for NUTS2 region j.[5] The random part of the model includes a linear time effect at all levels, so that the effect of time on productivity can be different at different spatial levels. These random intercept and slope terms are assumed to follow a bivariate normal distribution; for instance, at the NUTS0 (country) level:

$$\left(\mathrm{u}_{0j}, \mathrm{u}_{1j}\right) \sim \mathrm{N}\left(0, \Omega_{\mathrm{u}}\right), \text{ where } \Omega_{\mathrm{u}} = \begin{bmatrix} \sigma^2_{\mathrm{u}0} & \\ \sigma_{\mathrm{u}01} & \sigma^2_{\mathrm{u}1} \end{bmatrix}. \tag{3}$$

Thus, the between-country variance around the global-mean is given by a quadratic function in time:

$$\sigma^2_{u0} + 2\sigma_{u01}T_{ij} + \sigma^2_{u1}T^2_{ij} \tag{4}$$

which allows for between-country differences to increase, decrease or remain unchanged through time. The same statistical practice applies to the evolving differences at the NUTS1 and NUTS2 levels.

These covariance terms can be given a direct interpretation. A positive covariance statistic implies that geographical units with high productivity values grow faster than those with lower productivity values. In such a case, this would be synonymous with diverging productivity trajectories (i.e. divergence) at that particular geographical level once variation at other levels has been taken into account. Similarly, a negative covariance statistic means that geographical units with higher (lower) productivity at the start of the time period are growing relatively slower (faster) over time, which is tantamount to greater distribution homogeneity (i.e. convergence).

Group-based trajectory approach

A group-based trajectory statistical approach (see Nagin, 2005) can be implemented to identify distinctive groups of regions that follow similar productivity trajectories and can be applied to identify the productivity trajectories themselves.[6] This is different from and probably superior to the log *t* test (Philips and Sul, 2007) which has been applied to identify regional convergence clubs by Bartkowska and Riedl (2012) over the relatively short time period of 1990-2002. The novelty of Nagin's group-based modelling approach is threefold. First, the groups of regions with distinctive trajectories are not defined *a priori* but instead are conceived as *latent* and need to be identified. Therefore, this is an inductive approach which has considerable value for pattern-identification. Second, membership of groups is conceived probabilistically but not as an all-or-nothing deterministic outcome. In our case, the results show the probability that each region belongs to their respective identified group. Third, identification and estimation of groups, trends, probabilistic group membership, and

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5 We estimate the growth curve model using the *MLwiN* software (Rasbash *et al.* 2004; http://www.cmm.bristol.ac.uk).

6 Statistically, it allows identification of the risk factors to explain and modify these distinctive time-based progressions.

functional relationships are undertaken simultaneously and not via a sequence of separate models. This permits the estimation of a goodness-of-fit measure corresponding to the overall model and individual parameter standard errors estimates to indicate the degree of uncertainty.

Underlying our group-based trajectory model is the assumption that regions can be grouped into latent categories such that those in a given category have the same productivity trajectory. An unobserved indicator of group membership, Z_{jg}, is coded 1 if region *j* is in group *g* and 0 otherwise. Note that in our case this method could be applied to any data level: NUTS2, NUTS1 or NUTS0. The probability that region *j* belongs to group *g* is denoted by $\pi_j^{(g)} = \Pr(Z_j = g)$, where $g = 1, \ldots, \mathrm{G}$, with G signifying the total number of groups. The general structure of the model is illustrated in Figure 2 as a directed acyclic graph where the arrows indicate the relationship of the outcome variable as a function of each variable in the model. Y_{ij} is the productivity for region *j* in year *i*, which depends on a set of time variables, T_{ij} (usually as a set of polynomials).

{Insert Figure 2 here}

This model is appropriate when the expected value of Y changes smoothly as a function of the polynomial of time. Sharp changes can be handled through the inclusion of time-dependent covariates with dummy variables representing regime shifts. More formally, a growth trajectory model with a third order polynomial[7] of time can be written as follows:

$$
\begin{aligned}
&y_{ij}^{(g)} = \beta_{0j}^{(g)} Z_{jg} + \beta_1^{(g)} T_{ij} Z_{jg} + \beta_2^{(g)} T_{ij}^2 Z_{jg} + \beta_3^{(g)} T_{ij}^3 Z_{jg} + e_{ij} \\
&\beta_{0j}^{(g)} = \beta_0^{(g)} + u_j^{(g)} \\
&u_j^{(g)} \sim N(0, \sigma_u^{2(g)}) \\
&e_{ij} \sim N(0, \sigma_e^2)
\end{aligned}
\qquad (5)
$$

The βs in this model are regression coefficients which give the linear, quadratic and cubic relations between time and productivity.[8] The superscript *g* indexes the unknown groups, each with a potentially different set of estimated β terms and hence with distinctive trends. In the first equation there are two random terms which summarise the unexplained variation after the trends have been extracted. The between-region residual differences are represented by u_j and the within-region, between-occasion residual terms are represented by e_{ij}. Assuming a normal distribution with zero mean, these residual terms can be summarised respectively in variance terms $\sigma_u^{2(g)}$ and σ_e^2. The formulation adopted here allows each group of

[7] It is common practice in the latent growth literature for a third order polynomial to be used as this is complex enough to capture major trends but not too complex that it compromises the ability to fit models reliably with convergence.

[8] In each group, g, regional productivity trajectories are assumed to be a cubic polynomial function of year, T. Note that when compared to the multi-level time-series-cross-section regression, here we assume that, within a group, only the intercept of the trajectory varies across regions, and that the within-region variance is constant over time.

regions to have different degrees of residual variability, and this is why the variance terms have superscript g.

Procedures to fit this model have been implemented by Jones *et al.* (2001) in their *PROC TRAJ* procedure. Here, the censored normal is used to reflect the fact that productivity does not lie outside the €5,000 to €40,000 range (constant €2000). This procedure should be appropriate for continuous data that are approximately conditionally normally distributed (Nagin and Tremblay, 2001).

One restriction of the group-based approach is that the number of groups, G, must be specified in advance, although a diagnostic test can be used to identify an 'optimum' value. However, there is substantial debate over how to use test statistics to determine the number of groups to include in the model, as well as the specification of the order of the polynomial equation used to represent the shape of each group's trajectory (Ghosh and Sen, 1985; Titterington *et al*., 1985). Here, Nagin's (2005) recommendation is adopted, which is to use a Bayesian Information Criterion, calculated as:

$$BIC = \log(L) - 0.5k\log(N) + p \qquad (6)$$

where L is the model's maximized likelihood, N is the sample size and P is the total number of parameters in the model. The *BIC* is a 'badness' of fit measure which penalizes model complexity. An improved goodness of fit will be reflected in the likelihood; complexity is represented by the number of parameters, which are determined by the order of the polynomial used to model each trajectory and the number of groups. D'Unger *et al.* (1998) have shown that the change in the *BIC* between models is an approximation to the log of the Bayes factor, which gives the posterior odds that the alternative hypothesis is correct when the prior probability that the alternative hypothesis is correct equals one-half. Muthén (2003) emphasises that the *BIC* is not really an index for addressing a model's absolute goodness of fit, but instead is a relative fit measure comparing competing models.[9]

5. Results

Multi-level time-series-cross-section regression results

Application of model (1) to the GVA per worker-hour productivity data generates the following results:

[9] Model selection works inductively and in two stages. First, the models are fitted without any time-independent variables but including a third order polynomial of time for a single group, and the *BIC* is calculated. Then two groups are specified and the *BIC* obtained. Next, three groups are fitted then four, five and so on until there is no further reduction in the *BIC* which then signifies the most parsimonious model in terms of the number of groups with distinctive trends. It should be stressed that the classification is non-hierarchical, so that when an additional group is created this does not necessarily mean that only one of the previous groups is split. When three groups replace two, for example, it may well be not only that both of the two groups in the latter solution lose some members to the third group but that there is also some redistribution of members between the first two.

$\text{prodk}_{ijkl} \sim \text{N}(XB, \Omega)$

$\text{prodk}_{ijkl} = \beta_{0ijkl}\text{cons}$

$\beta_{0ijkl} = 15.946(1.928) + f_{0l} + v_{0kl} + u_{0jkl} + e_{0ijkl}$

$$\left[f_{0l}\right] \sim \text{N}(0, \Omega_f) : \Omega_f = \left[63.591(22.293)\right]$$

$$\left[v_{0kl}\right] \sim \text{N}(0, \Omega_v) : \Omega_v = \left[5.197(1.244)\right]$$

$$\left[u_{0jkl}\right] \sim \text{N}(0, \Omega_u) : \Omega_u = \left[2.805(0.347)\right]$$

$$\left[e_{0ijkl}\right] \sim \text{N}(0, \Omega_e) : \Omega_e = \left[6.709(0.124)\right]$$

*-2*loglikelihood(IGLS Deviance)* = 29513.465(6064 of 6524 cases in use)

These results highlight a number of important issues. First, the intercept illustrates that the initial position of productivity for each region influences their pattern over the time period (15.946, s.e. 1.928). This is suggestive that path dependence is important in a region's evolution and is akin to Martin and Sunley's (2006) argument. Second, labour productivity per worker-hour values change at different rates over our 1980-2007 time period. Third, there are highly statistically significant positive variance estimates across all spatial levels. This implies that there are large and significant differences in labour productivity per worker-hour at NUTS0 (i.e. f_{0l}), NUTS1 (v_{0kl}) *and* NUTS2 (u_{0jkl}) levels. The novelty of this part of the research is that we have moved away from the standard discussion in the literature of global-means and are explicitly emphasising that the heterogeneity in the sample is an important facet of the data.

Application of model (2) to the data effectively extends the above results to include a time element. This permits an analysis to identify whether the results presented above evolve over time, and it generates the following results:

$$\text{prodk}_{ijkl} \sim \text{N}(XB,\ \Omega)$$
$$\text{prodk}_{ijkl} = \beta_{0ijkl}\text{cons} + \beta_{1jkl}(\text{year-94})_{ijkl}$$
$$\beta_{0ijkl} = 15.995(1.986) + f_{0l} + v_{0kl} + u_{0jkl} + e_{0ijkl}$$
$$\beta_{1jkl} = 0.283(0.031) + f_{1l} + v_{1kl} + u_{1jkl}$$

$$\begin{bmatrix} f_{0l} \\ f_{1l} \end{bmatrix} \sim \text{N}(0,\ \Omega_f) \ : \ \Omega_f = \begin{bmatrix} 66.699(23.663) & \\ 0.725(0.316) & 0.015(0.006) \end{bmatrix}$$

$$\begin{bmatrix} v_{0kl} \\ v_{1kl} \end{bmatrix} \sim \text{N}(0,\ \Omega_v) \ : \ \Omega_v = \begin{bmatrix} 7.048(1.578) & \\ 0.040(0.030) & 0.003(0.001) \end{bmatrix}$$

$$\begin{bmatrix} u_{0jkl} \\ u_{1jkl} \end{bmatrix} \sim \text{N}(0,\ \Omega_u) \ : \ \Omega_u = \begin{bmatrix} 2.983(0.339) & \\ 0.046(0.011) & 0.006(0.001) \end{bmatrix}$$

$$\begin{bmatrix} e_{0ijkl} \end{bmatrix} \sim \text{N}(0,\ \Omega_e) \ : \ \Omega_e = \begin{bmatrix} 0.390(0.007) \end{bmatrix}$$

*-2*loglikelihood(IGLS Deviance)* = 13723.161(6064 of 6524 cases in use)

A number of important points can be identified. First, the intercept illustrates that the initial position of productivity for each region influences their pattern over the time period, which again suggests that path dependence is important in a region's evolution. Second, labour productivity per worker-hour values continue to change at different rates over our 1980-2007 time period, which will primarily capture the business cycle.

Third, there remain statistically significant variations across all data levels, as evidenced by the f_{0l}, v_{0kl}, u_{0jkl} and e_{0ijkl} residual estimates. It is opportune to note that the variance estimates at each level have increased slightly relative to the previous estimates, and this probably reflects that previous estimates were biased downwards due to the omission of important temporal changes in productivity that occurred asymmetrically at different spatial levels.

Fourth, the time variable appropriate for each level is statistically significant, as can be seen by the f_{1l}, v_{1kl} and u_{1jkl} residual estimates. These illustrate that productivity per worker-hour values evolve over time at each particular spatial level, and hence should not be assumed to be constant as would be the case when applying fixed or random effects estimation techniques.

Fifth, and most important from a policy perspective, the residual estimates co-vary with each other at the different spatial scales. The variance-covariance estimate at the NUTS0 (country) level is positive and statistically significant [0.725, s.e. 0.316]. It suggests there is a tendency towards national-level divergence in productivity per worker-hour once productivity and time have been integrated into the model at the different spatial scales; there is certainly no indication of convergence at the national level as is ingrained in the literature using the more traditional, non-hierarchical regression approach that typically holds unobserved heterogeneity constant over time. The same qualitative observation can be made at the NUTS1 level, i.e. a positive variance-covariance statistic, albeit not statistically different from zero, which again does not corroborate traditional, non-hierarchical regression approaches that suggest the presence of regional convergence (0.040, s.e. 0.030).

Sixth, the positive and highly statistically significant variance-covariance statistic at the NUTS2 spatial scale indicates that there is strong divergence of labour productivity per worker-hour, or put another way, there is a large amount of variation in the time series paths of NUTS2 regional productivity per worker-hour (2.983, s.e. 0.339) and that this variation has been increasing over time (0.046, s.e. 0.011). They imply that there was strong divergence in the distribution of labour productivity across NUTS2 regions of Europe.

These results imply that the labour productivity per worker-hour at the NUTS2 distribution is fanning out, implying that any global-mean regression line will have standard errors of prediction lines that are diverging from the global-mean regression line in absolute and real terms, and hence any forecasting undertaken with standard regression approach will be increasingly off the mark. Profiles of the evolving variance estimates at NUTS0, NUTS1 and NUTS2 spatial scales are presented in Figure 3: they emphasise the presence of divergence at all levels. In addition to noting that divergence occurred consistently over the time period for the larger spatial scales, it is interesting to note that there is a hint that convergence occurred at the NUTS2 level in the early 1980s, and the causes of this difference is worthy of future research.

{Figure 3 about here}

Group-based trajectory approach – National data

The next stage of our investigation is to identify whether groups of regions are following distinct productivity per worker-hour trajectories which differ statistically significantly between groups. Applications of models (5) and (6) to NUTS0- (country) level data reveal the presence of five groups. These are expressed in productivity trajectories in Figure 4[10] and the groups members are listed in Table 2.

{Figure 4 about here}
{Insert Table 2 here}

The analysis reveals the presence of five groups of countries that are diverging in absolute terms across the entire distribution. The gap between the richest, most productive group of countries (group 5) and the other groups increased over the 1980s, and there is no evidence that this gap closed with any of the other groups over the rest of the time period under study. The gap between group 5 and the poorest, least-productive set (group 1) increased in absolute differences over time. There is evidence of a multi-speed Europe with the geographical core countries included in groups 3, 4 and 5 experiencing faster rates of productivity growth compared with their geographically-peripheral neighbours across the Mediterranean (group 2) and across Eastern Europe (group 1). Luxembourg, Norway, Denmark and Switzerland (group 5), which each have idiosyncratic reasons why they would grow faster than the average, appear to be slightly ahead of the larger countries of the rest of core who

[10] The profiles represent the growth trajectory of the regions within the club and the profile's intercept is based on the average starting value of productivity across this club's sample. Although all regions within the club grow at a very similar rate as denoted by the profile slope, around this line is a spread of regions that vary in distance from this mean-average trend line.

occupy groups 3 and 4. Note that the gap between groups 3 and 4 is relatively small and the main difference appears to be a relatively slow growth rate in the 1980s and mid-2000s that differentiate these two groups.

Groups 1 and 2 have experienced similar productivity trajectories over this time period and but are diverging in absolute terms from the other groups; this cleavage appears to be a growing concern. Even before the current economic crisis, there is evidence that Greece and Spain were diverging downwards toward a low productivity basement.[11]

Group-based trajectory approach – Sub-national data

National level trends that reflect different productivity groups may be concealing sub-national evolutions. For example, there are many examples of parts of national economies that are sometimes performing poorly (e.g. Cornwall, England) or well (e.g. Paris, France) in terms of productivity relative to the rest of their nations.[12] There are also examples of border regions that may be inherently entwined into the economy of their national neighbours (e.g. Basque country, Spain). Analysis of labour productivity at the more disaggregated regional level may therefore permit the analysis of regional productivity groups.[13] This section should be viewed in the light of the significant divergence identified to be occurring over time at the NUTS0 and NUTS2 levels that were observed in Figure 3.

It is reasonable to argue that the application of the group-based trajectory approach to NUTS2 level productivity data should include a spatial weight to account for spatial spillovers between contiguous or proximate regions; this argument could apply to most entities that have a spatial element. Such an approach would permit an analysis that would purposefully lend itself to policy makers and to define the areas over which a similar set of policies could rule. However, as the analysis presented here is not in accordance with this specific policy aim and in order to maintain total flexibility in the empirical approach by permitting each and any NUTS2 region to be groupbed with any other NUTS2 area, the decision is taken not to incorporate a spatial weights matrix. Moreover, Harris and Kravtsova (2009) warn against the standard approach in the spatial econometrics literature of imposing spatial weights matrices that use contiguous or distance-related measures to weight observations. This is because such an approach would impose a structure of spatial interactions that is untested and potentially misspecified and because it can misspecify and bias the non-spatial parameter estimates. In our regional-level productivity case, capturing economic distance, which varies enormously in importance across different types of goods, infrastructures and markets, is extremely problematic because i) we do not have any prior assumptions about the form of spatial dependence and ii) the imposition of a spatial weights matrix collapses all spatial interactions into a single weighted variable, rather than directly testing whether and how much regions interact with each other. Of course, it is possible to adjust spatial weights matrices to capture a

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11 Our time period is not long enough to be able to identify conclusively whether they are strongly converging with the accession countries at the basement of Europe's productivity distribution.

12 It is possible that these are outcomes of the Modifiable Areal Unit Problem; see Openshaw (1983).

13 A similar analysis could be performed at the NUTS1 level, but we omit it here for brevity.

particular structure of spatial interaction but in our case this would be atheoretical, untested and potentially could lead to misspecification.[14]

Application of the group-based trajectory approach to NUTS2 level productivity data reveals the trajectories of six groups, as presented in Figure 5 with group membership tabulated in Table 2. It should be emphasized that all group membership effects are statistically significant suggesting that there are productivity trajectory characteristics of the members of these groups that are significantly different from those regions in other groups. Several observations are worthy of greater emphasis. First, in line with the NUTS0 national level results, the NUTS2 regional analysis is not consistent with convergence across the sample; the gaps between the initial positions of the trajectories is smaller than the gap at the end of the period. Second, there is evidence of emerging cleavages between groups. Groups 6 and 5 began diverging in the late-1980s. Regions in group 6 grew faster than any other regions in the top half of the distribution while regions in group 5 deteriorated and converged to the growth rate of the regions in group 4. Third, in general, groups 6, 5 and 4 increased their productivity rates faster and diverged away from groups 3, 2 and 1, which could be behind some studies claim of a duel-speed Europe.

Fourth, although the trajectories for groups 1 and 2 began in roughly the same starting position, regions in these two groups grew are startlingly different rates. Those regions in group 1, primarily from Eastern Europe but also from Portugal, experienced a fall in their productivity levels which only began to recover in the early 1990s. In contrast, regions in group 2 grew first fairly slowly but then began to grow relatively fast in the 2000s; out of sample anecdotal observation of these countries (which includes Spain, Greece and Portugal) may lend us to believe that some of these regions grew unsustainably fast. Although the large cleavage between groups 1 and 2 would be a concern for the policy makers of the NUTS2 regions in group 1, they may have implemented policies that enable them to grow more sustainably in the future. These results differ from those provided by Vojinović and Próchniak (2009) who analysed data from 1992 to 2006 and found divergence in the early 1990s. We find that these regions strongly diverged in the 1980s and did not follow a clear trajectory of convergence with other regions of Europe in our sample.

{Insert Figures 5 and 6 here}

Finally, although there is evidence in Table 2 that some countries have regions that are growing at very similar rates and hence those regions are members of the same group (e.g. regions within Italy, Sweden and UK) there is also evidence that some countries have regions that are members of distinctly different groups. For instance, most of the NUTS2 regions of France are part of group 5, but there is a clear set of contiguous regions that are part of group 4 (from Brittany to Poitou-Charentes to Auvergne) and with the global city region of Paris being part of group 5. Other examples of globally-relevant conurbations doing better than the rest of their home countries include London, Stockholm and Vienna. Membership of a higher group by important leading conurbations may be due to the stronger trade linkages and greater agglomeration economies. The opposite effect could be the reason why areas like Cornwall (UK), Extremadura (Spain) and Gelderland (The Netherlands) lag behind the rest of their home countries.

[14] Fingleton (2003) asks “what is the theoretical and empirical basis of assumptions about the spatial reach of externalities, and how can this be enhanced?” Throughout, the empirical results presented in this paper are not adjusted for any spatial weights matrix.

The evidence presented above contradicts the majority of the literature which suggests productivity convergence across European regions. Instead, the evidence presented above highlights the strong tendency towards divergence. It emphasises that there are many different speeds of growth that different regions are experiencing, that there are productivity trajectories that are common across countries and that it is not necessarily the case that all regions within a country follow the same growth path. This reality check should spur more research that attempts to identify why regions at different spatial scales grow at different rates and why spatial spillovers do not fully eliminate gaps in productivity trajectories that could harmonise standard of living.

6. Conclusions

This paper has examined productivity dynamics at different spatial scales across the European Union and has assessed whether there are groups of regions that are following similar productivity trajectories over time. Instead of applying a theoretical model that incorporates an explicit term to capture convergence, this paper has presented the results of multilevel regression that permits simultaneous modelling of data at different geographical scales and permits an analysis of how the variance at difference spatial scales co-varies with time. This reality check reveals evidence of divergence at all spatial scales (NUTS0, NUTS1 and NUTS2) since at least the early 1990s.

The paper has also presented the results of applications of non-parametric group based trajectory techniques and these reveal the presence of a multi-speed Europe with regions within countries following at different growth trajectories thereby resulting in divergence within countries. Membership of these growth trajectory groups is not confined by national border. Taken together, these results provide strong evidence that in terms of productivity we have a multi-speed Europe.

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Table 1: Number of NUTS1 and 2 Regions for each of 29 Countries: 1980-2007

Country	NUTS1	NUTS2
Austria	3	9
Belgium[7]	3	9
Bulgaria[1]	2	0
Cyprus[1]	1	0
Czech Republic[1]	1	8
Germany[2]	16	40
Denmark	1	3
Estonia[1]	1	0
Spain	7	16
Finland	1	5
France[3]	8	22
Greece	4	13
Hungary[1]	1	7
Ireland	1	2
Italy	5	20
Lithuania[1]	1	0
Latvia[1]	1	0
Malta[1]	1	0
The Netherlands[4, 6]	4	10
Poland[1]	6	16
Portugal[5]	1	5
Romania[1]	1	0
Sweden	3	8
Slovenia[1]	1	0
Slovakia[1]	1	4
UK[6]	12	36
Luxembourg	1	0
Norway	1	0
Switzerland	1	0
Total	**90**	**233**

Source: Cambridge Econometrics (2009).

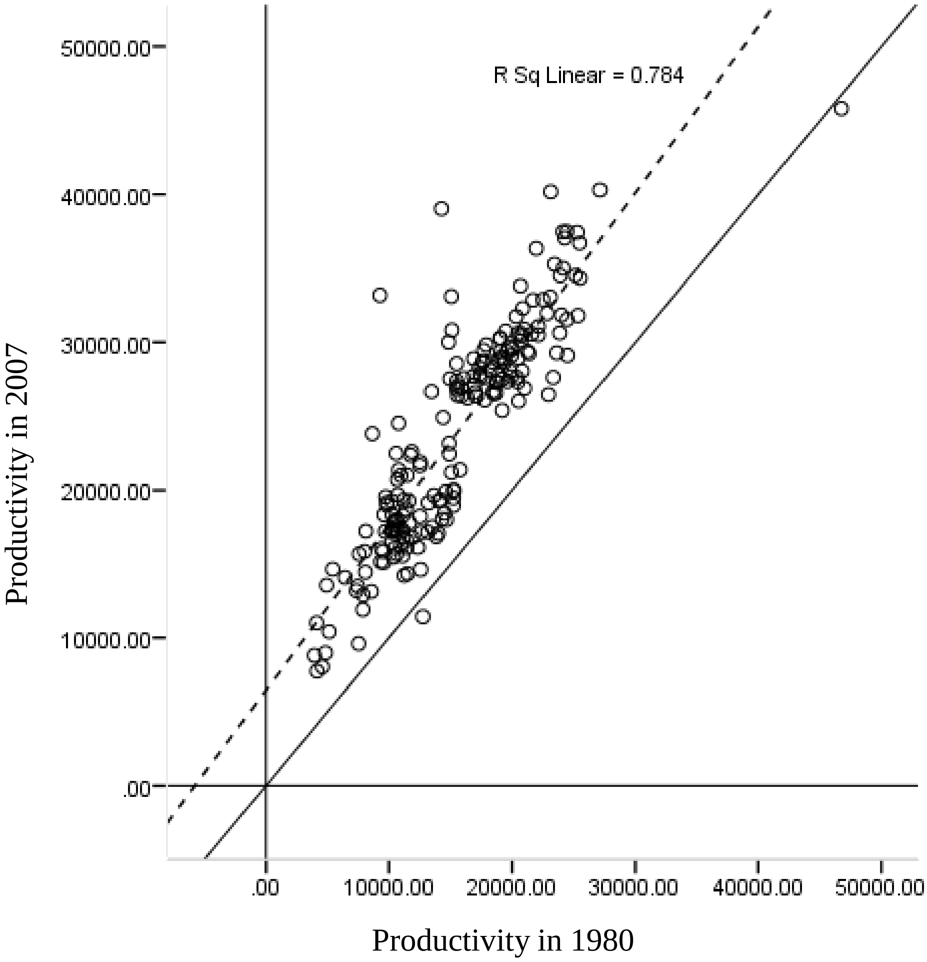
Notes
1: Available from 1990
2: 5 NUTS1 and 8 NUTS2 regions in the former East Germany available from 1990.
3. Excluding 4 overseas regions.
4: *Flevoland* available from 1985.
5: Excluding 2 overseas regions.
6: *Groningen* in the Netherlands and *North-Eastern Scotland* in the UK are excluded because of the influence of North-Sea oil (see Neven and Guoyette, 1995).
7: Belgium excludes Vlaams Brabant and Brabant Wallon

Table 2: NUTS0 group membership and NUTS2 group membership

	NUTS0 group	NUTS2 group					
		1	2	3	4	5	6
Denmark	5					√	√
Luxembourg	5						
Norway	5						
Switzerland	5						
Belgium	4					√	√
France	4				√	√	Ile de France
The Netherlands	4				Gelderland Limburg	√	Utrecht Noord-Holland Zuid-Holland
Sweden	4				√	Stockholm	
Ireland	4			√	√		
Austria	3				√	√	Vienna
Finland	3				√	√	
Germany	3			√	√	√	√
Italy	3			√	Lombardi		
UK	3		Cornwall East Wales	√	London		
Cyprus	2						
Malta	2						
Slovenia	2						
Spain	2		Galicia Castilla-la Mancha Extremadura	√			
Greece	2		√				
Portugal	2	√	√				
Bulgaria	1						
Czech Rep	1	√					
Estonia	1						
Hungary	1	√					
Latvia	1						
Lithuania	1						
Poland	1	√					
Romania	1						
Slovakia	1	√					

Note: √ implies regions from the respective country are identified as being within a particular NUTS2 group, and region names are listed when they are outliers for the country. NUTS0 and NUTS2 groups follow different trajectories and are estimated separately. Hence it is entirely possible that a country could be classified in a NUTS0 group with one number and have the majority if not all its constituent NUTS2 parts in a group with a different number.

Figure 1: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50000.00
40000.00
30000.00
20000.00
10000.00
.00
Productivity in 2007
.00
10000.00
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30000.00
40000.00
50000.00
Productivity in 1980

Figure 2: Directed acyclic graph of the group trajectory model

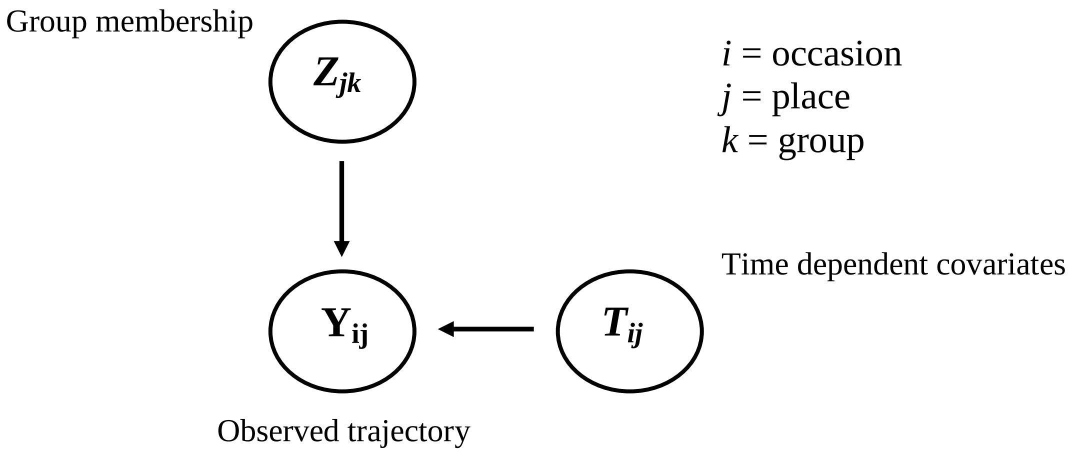
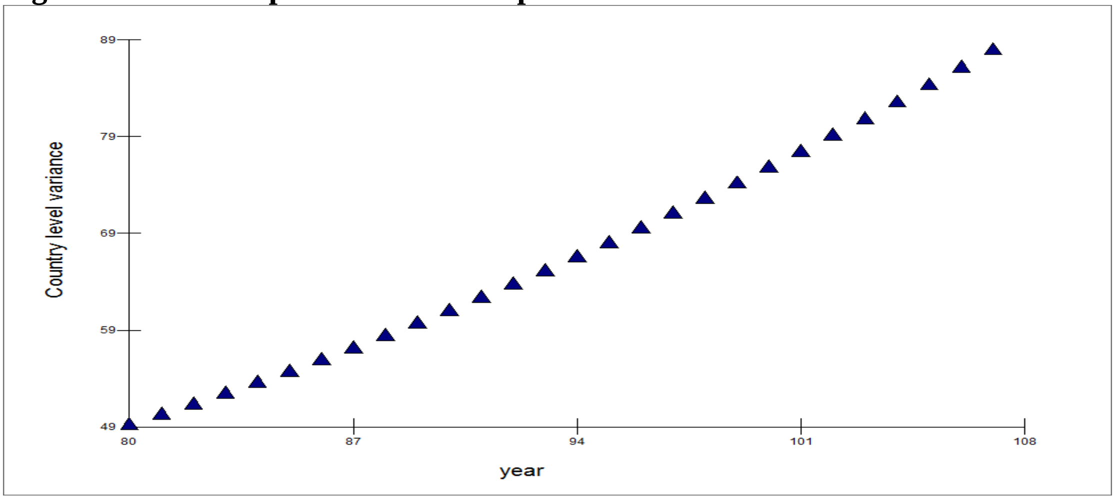
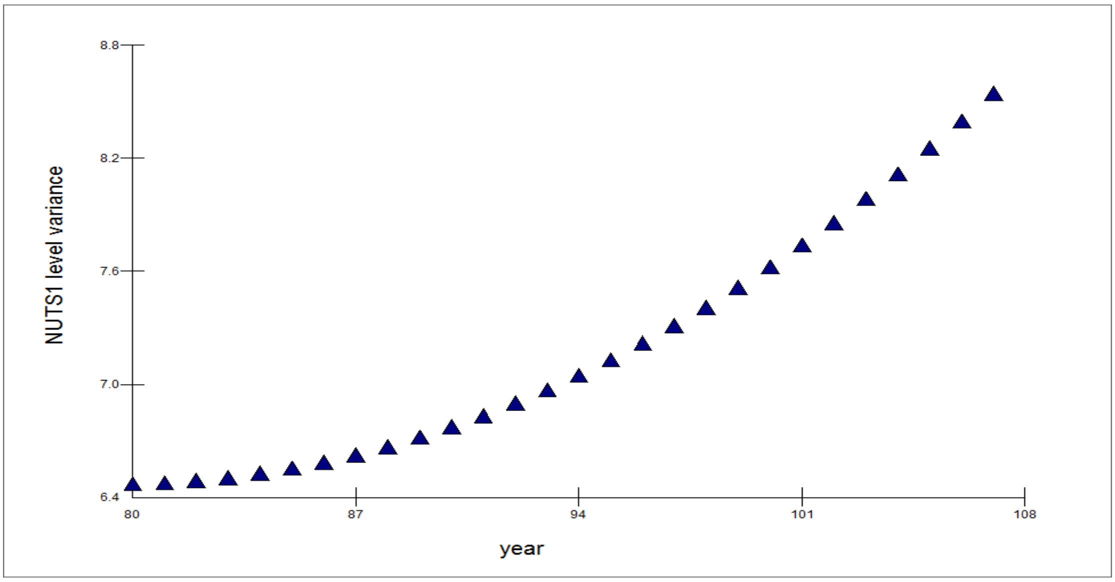


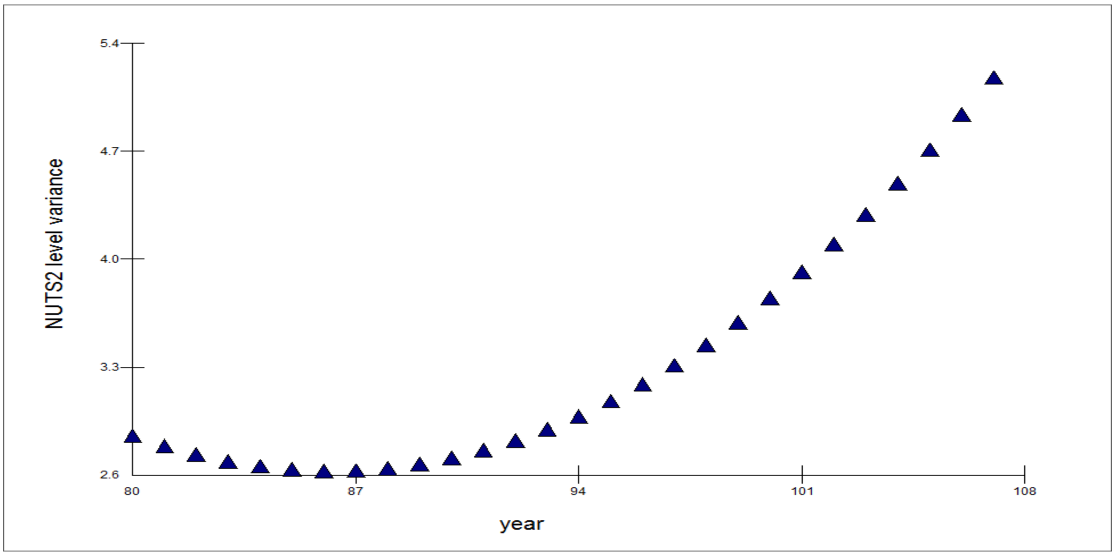
Figure 3: Variance plots at different spatial scales



NUTS0 – country level



NUTS1 – regional level



NUTS2 – sub-regional level

Figure 4: NUTS0 group trajectories

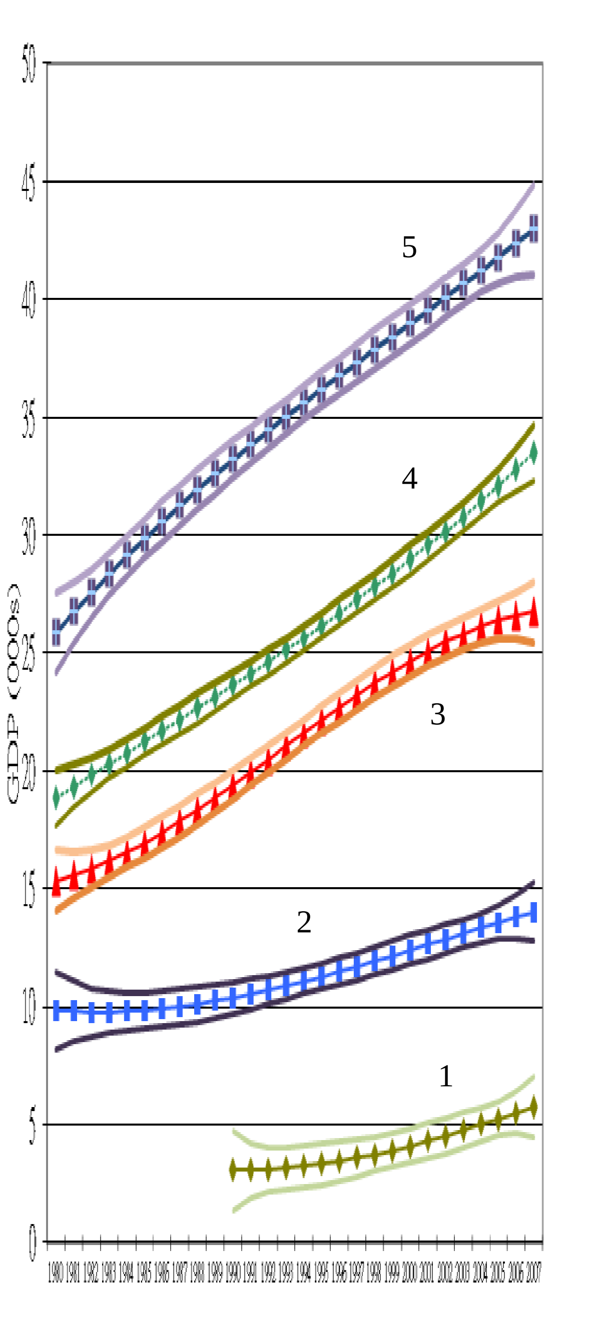


Figure 5: NUTS2 group trajectories

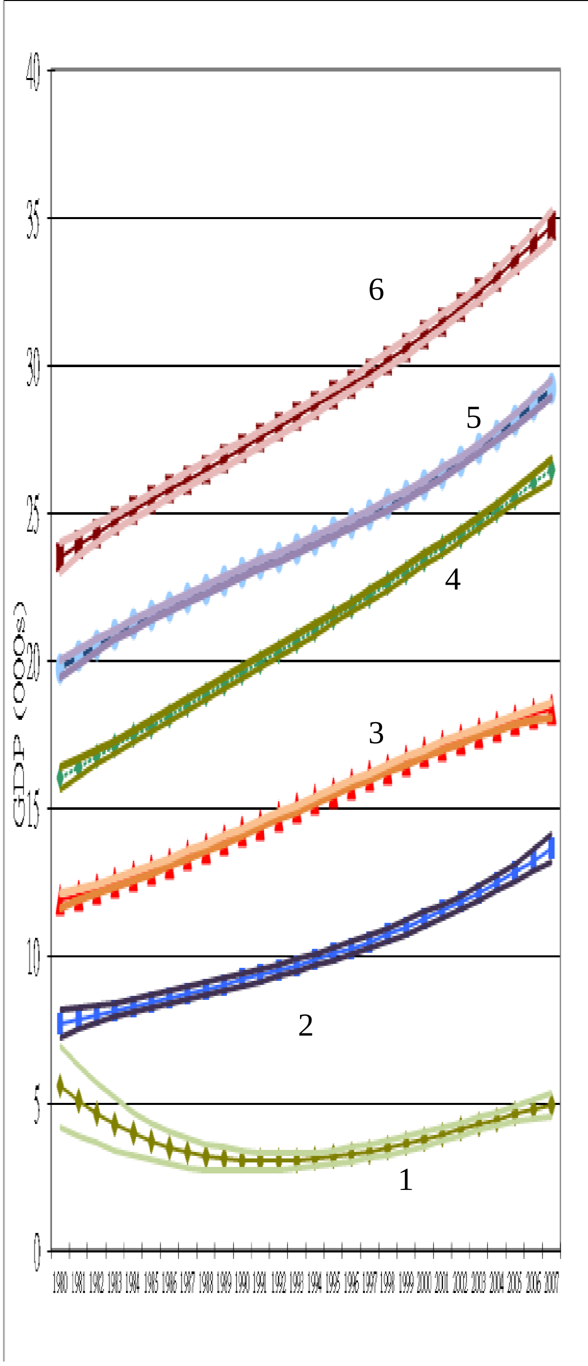
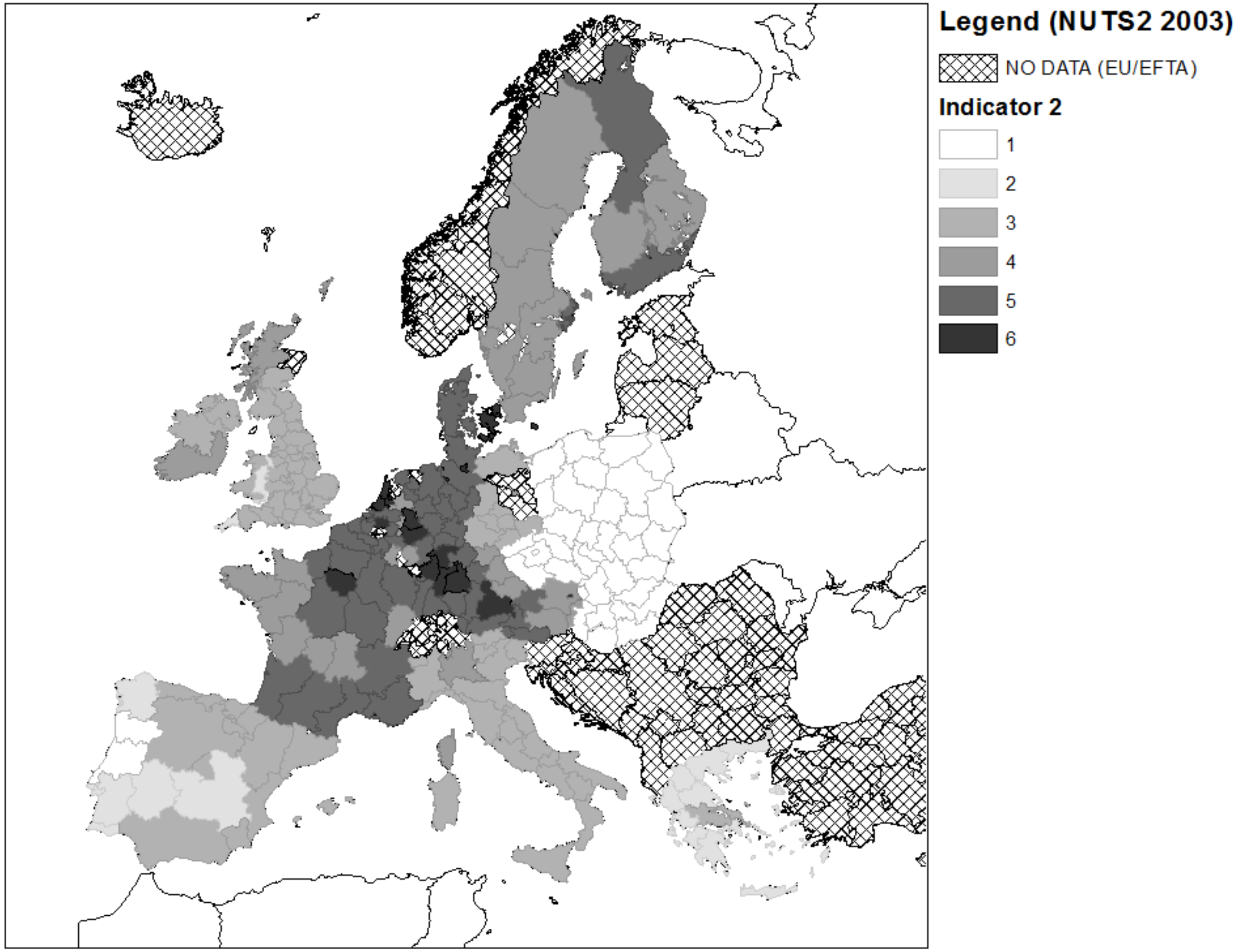


Figure 6: Map showing relative location of group members



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