Does Distance Matter for Economic Performance? Evidence from European Regions*

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Abstract

We present evidence that whilst both long-term and cyclical movements in regional output within the European Union are geographically clustered this clustering is linked not to geographic location *per se* but to membership of a country.

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1. Introduction

Casual observation suggests that long-run growth and cyclical movements in output exhibit some degree of spatial correlation: an economy - whether it is defined as a country, a state, or a region[1] - which is currently experiencing, for example, a cyclical downturn is more likely than not to be situated close to other economies which are themselves currently experiencing a downturn; and an economy which has experienced, for example, a long period of high growth is more likely than not to be situated close to other economies which have enjoyed high long-term growth. An obvious example of this clustering of both long-run and short-run output movements at the country level is provided by the Asian tiger economies which, throughout the 1970s, 1980s and early 1990s, experienced exceptionally high average or long-term growth, and most of which suffered an exceptionally severe cyclical downturn in the late 1990s. At the regional level examples of clustering are provided by the Italian mezzogiorno, the economic performance of the North of England (Armstrong, 1991) and the Spanish interior (Critz, 1995), although evidence against clustering within the UK can be found in Chatterji and Dewhurst (1996). Armstrong (1995), Cheshire and Carbonaro (1995), Quah (1996), and Clark and Wincoop (1999) suggest there is also clustering of regional economic performance within Europe as a whole.

There are several reasons why economic activity might be clustered, some of which emphasise the role of geographic distance *per se*. For example, Krugman (1991a and b) shows that if transport costs vary with distance (as in Samuelson's "iceberg" model) internal economies of scale can encourage a clustering of industrial activity. Firms clustered in this way are likely to establish trading links with each other and so exhibit some degree of similarity in their cyclical behaviour. A mechanism that will encourage clustering of longer-run growth is the presence of externalities to learning (Lucas, 1988; Benabou, 1996): such external effects are inherently more likely to affect people who are geographically close than those who are distant and there is some empirical evidence to suggest that firms prefer to be close to the sources of technical knowledge (Gertler, 1995). So clustering in both short- and long-run output movements may be due to geographic distance *per se*.

However, links between firms, workers etc. may be more influenced by institutional factors than by distance itself (Lundvall, 1988). In the European context, distance may be less important than national and linguistic boundaries since externalities are most likely to arise when information can be easily transmitted and understood. Thus it may be that "physical distance is really just a proxy for cultural distance, where ‘culture’ refers to a set of dominant workplace practices shaped in large part by legislative definitions of employment relations and the nature of the (public and private) industrial training system.” (Gertler, 1995). More generally, cultural, historical and institutional differences - “cultural distance” - can act as a barrier to the geographic forces for clustering mentioned above whilst cultural proximity can be an alternative cause of clustering.[2]

Of course, over different scales the relative importance of geographic and cultural distances may vary. Moreno and Trehan (1997), for example, find that distance is important in explaining global clustering of long-term economic growth. At the other extreme there is evidence that clustering of businesses in Europe only occurs at an extremely local level (Storper, 1993; special issue of Regional Studies, 1999).

This paper is an attempt to test the relative importance of geographic and cultural distance in causing the clustering of both cyclical and long-term movements in regional per capita GDP within a number of countries of the European Union. Our data are observations on cyclical and long-term output movements in more than 100 (NUTS2) regions from twelve current EU countries over the period 1980-1996. This data set is a particularly promising one in that membership of a European nation state implies a large degree of similarity in culture, history and legal and other institutions. If geographic distance is significant in accounting for any observed clustering of long-term and short-term output movements across EU regions, that significance should be robust against conditioning on membership of a nation state with all the cultural similarity that such membership implies.

Our results strongly suggest that, whilst the long-term and cyclical behaviour of output in EU regions do both exhibit clustering, geographic proximity is not a significant cause of it: once membership of a nation state is allowed for, neither the long-term nor cyclical behaviour of a region is significantly affected by the economic performance of the geographically closer regions. We also find little evidence that the role of geographic distance has increased - or the role of nationality decreased - over the period we consider. Since membership of the EU implies an absence of tariff barriers and since tariff barriers might have inhibited the influence of geographically close regions which are in different countries, it might be

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[1] We use the term “region” to mean part of a nation state. In our empirical work we use it to mean a NUTS2 region within Europe.

[2] An example of the potential role of national boundaries is provided by Engel and Rogers (1996) who, in their analysis of price movements, find that crossing the US-Canada border is equivalent to travelling 1,780 miles.

expected that in the later period, when the absence of tariff barriers has had more time to exert its effects, the role of geographic proximity would be stronger. Our failure to find any such effect argues against the importance of geographic as against cultural distance.[3]

The paper has three main sections: in the first we explain our methodology; in the second we apply this methodology to the long-run behaviour of output in European regions and report our results; and in the third we present the results of applying this methodology to the short-term behaviour of European regional output.

2. *Methodology*

Figure 1a presents the average percentage rates of growth of per capita output over the period 1980-1996 for the 11 regions that make up the UK; figure 1b presents the same variable for 11 "regions" of Europe: (the Grand Duchy of) Luxembourg and the 10 regions closest to it (which are in four different countries).[4] The figures suggest that the regions of the UK are much more similar in their long-run growth than are those regions of Europe geographically clustered around Luxembourg: the standard deviation of the growth rates across the UK is 0.51, whereas across the regions close to Luxembourg it is 1.06.

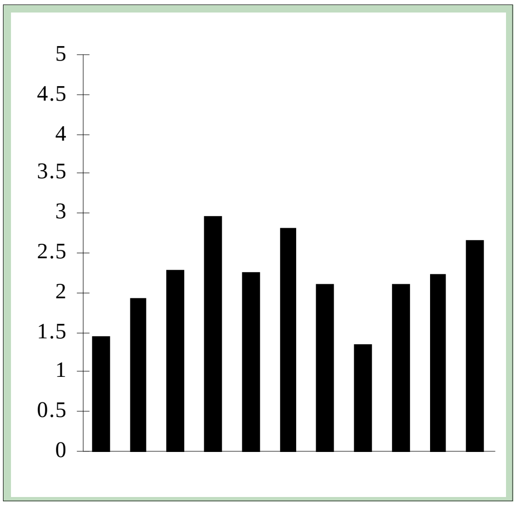


Figure 1a Long-run growth in UK regions

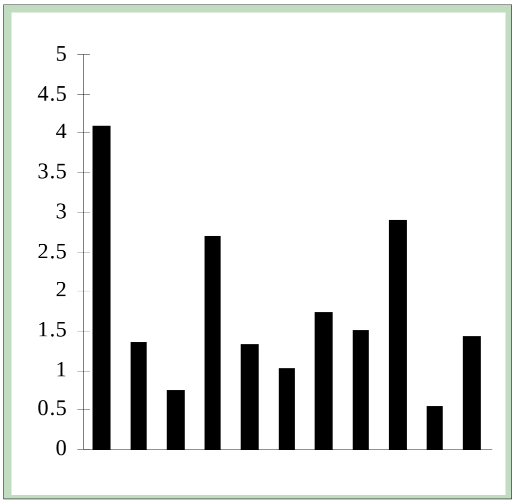
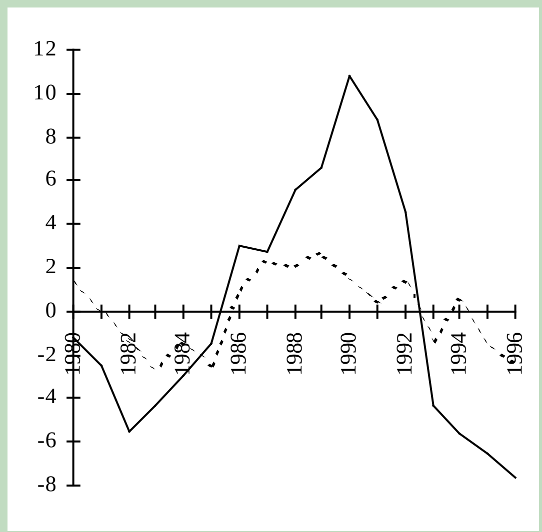


Figure 1b Long-run growth in regions close to Lux.

Figure 2a presents the percentage deviation of output from its log-linear trend over the period 1980-1996 for two regions of Europe which are geographically close but in different countries: Strasbourg (France) and Stuttgart (Germany). Figure 2b presents the same variable for two regions which are in the same country but geographically more distant: Strasbourg

[3] Non-tariff barriers have been removed too but whilst much of the important legislation took place in the late 1980s the removal of such barriers did not really begin until near the end of our data period.
[4] We describe the data and our method of calculating distances between regions more fully below. The regions are defined generally at the NUTS2 level.

and Marseilles. These two figures suggest a greater influence of geographic proximity on output: the contemporaneous correlation between output deviations in the two geographically close regions is 0.74, but only 0.54 in the two regions of the same country which are geographically more distant.



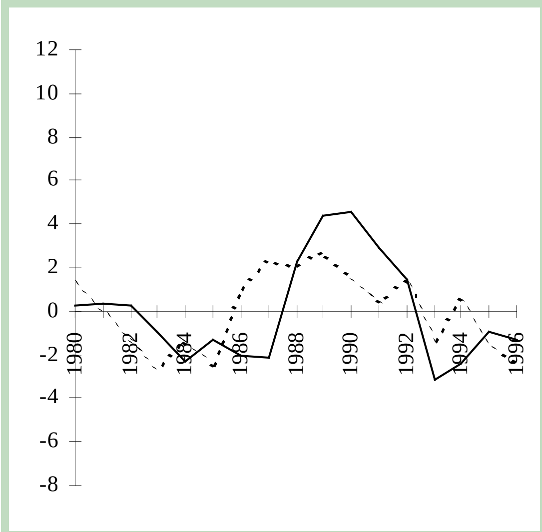


Figure 2a Cyclical movements of output: Strasbourg (---) and Stuttgart (__)

Figure 2b Cyclical movements in output: Strasbourg (---) and Marseilles (__)

Of course, there are a large number of regions which one could compare, and different regional comparisons might well suggest quite different things about the relative importance of geographic and cultural proximity on long-term and short-term movements in output. To be more systematic we apply the methodology used by Moreno and Trehan (1997) and explained in Anselin (1988) to assess the role of geographic distance on the long-run growth performance of countries of the world. We explain it and apply it first in the context of assessing the importance of geographic versus cultural distance in the clustering of *long-term* movements in EU regional output; then we adapt it and apply it to the problem of explaining the clustering of *cyclical* movements in output within the EU.

Let g_i represent the long-run per capita growth rate in region *i*, and let *G* represent a vector comprising observations of g_i on *n* regions. And let *W* represent an $n \times n$ matrix of weights. A typical element of *W*, w_{ij}, is an indicator of the importance of region *j* for region *i* and, as we shall explain below, depends upon the geographic distance between the two regions in such a way that the greater the distance between them the lower the weight; $w_{ij} = 0$ if $i = j$.

Our test of the influence of geographic as against cultural proximity on long-term movements in regional output is primarily based on estimates of versions of the following:

$$g_i = \rho \sum_{j=1}^{n} w_{ij} g_j + \sum_{k=1}^{K} \beta_k X_{ki} + \varepsilon_i \quad i = 1, \ldots n \qquad [1a]$$

or

$$[I - \rho W]G = X\beta + \varepsilon \qquad [1b]$$

where X is an $n \times K$ matrix of other influences on the growth rate; β is a $K \times 1$ vector of coefficients; ε is an $n \times 1$ vector of error terms assumed to be distributed $N(0, \sigma^2 \mathrm{I})$. The parameter ρ is of special interest. If geographic proximity *per se* is important then ρ should be positive and statistically significant even when other variables are included in the X matrix: in particular, its significance should be robust against the conditioning on membership of a nation state implied by the inclusion of country dummy variables in the X matrix where the inclusion of such dummies can be seen as conditioning on "cultural" distance.

We base the distance weights on the great circle distances between each region. The definition of a representative element of W, is:

$$w_{ij} = \left(\frac{1/d_{ij}}{\sum_j (1/d_{ij})} \right) \text{ if } i \neq j \qquad [2]$$

$$w_{ij} = 0 \text{ if } i = j$$

where d_{ij} is the great circle distance between regions i and j.[5]

Because the growth rate of each region can be affected by the growth rates of the other regions, OLS estimates of [1b] would not be consistent. We therefore obtained maximum likelihood estimates of [1b] by numerically maximising the following log likelihood with respect to the model's parameters:[6]

$$L = -(n/2)\ln\pi - (n/2)\ln\sigma^2 + \ln|I - \rho W| - \varepsilon'\varepsilon / 2\sigma^2 \qquad [3]$$

[5] This definition of the weights, which forces the weights to sum to one, amounts to assuming that it is *relative* rather than *absolute* distance which matters. We report below the results of dropping this assumption.

[6] For this we used GAUSS 's (1994) optimisation applications.

Equations [1b]-[3] provide the basic methodology for the results we present below but we also considered a number of variants. In the first set we redefine the weights themselves in a number of ways. First we define each weight as the numerator in equation [2], so $w_{ij} = 1/d_{ij}$: this allows *absolute* rather than *relative* distance to determine the weighting factor. Secondly, in calculating the weights, we first we multiply the inverse of the distance by the ratio of region *j*'s and region *i*'s output so that for $i \neq j$ $w_{ij} = \frac{(1/z_{ij})}{\sum_{j=1}^{n} 1/z_{ij}}$ where $z_{ij} \equiv (1/d_{ij}) y_j / y_i$ and y_j is region *j*'s GDP: this allows the relative economic size of regions to be important. And thirdly we first multiply the inverse of the distance by the ratio of region *j*'s and region *i*'s *per capita* output: this allows the relative standard of living of other regions to play a role.

In a second set of variations we distinguish between the effects on a region's growth rate of the *innovations* and of the *systematic movements* in other regions' growth rates - distance-weighted in each case. More formally we test for the influence of the distance-weighted *systematic movements* by testing for the significance of ρ in the following model,

$$G = [I - \rho W] X\beta + \varepsilon \qquad [4]$$

And we test for the influence of the distance-weighted *innovations* by testing for the significance of ρ in the model,

$$G = X\beta + [I - \rho W]\varepsilon \qquad [5]$$

3. Geographic proximity and long-term growth

In estimating the various models explained in the previous section we define g_i as either the average rate of growth of per capita GDP over the period 1980-1996, or as the average rate of growth over the period 1990-1996. In the former case we have observations on 142 regions and in the latter 146; in both cases the regions are drawn from twelve countries which are currently members of the EU.[7] The *X* vector is defined in five ways: in model I it consists of

[7] The source for our data is the Eurostat data set at rcade at the University of Durham. See the data appendix for a fuller account of each variable. The 12 countries are: Belgium, France, Germany, Italy, Luxembourg and the Netherlands, all of whom have been members of the EU or its predecessor since

only a constant; in model II it consists of a constant and the log of the initial level of the real per capita income in each region;[8] in model III it consists of the same variables as in model II but with a set of 11 zero/one country dummies; in model IV it consists of the same variables as in model II but with some allowance for differences in the economic structure of regions by the inclusion of the shares of output in each region accounted for by agriculture and services; model V is the same as model IV but with 11 country dummies. Where the "economic structure" variables are included, lack of available data meant that the number of regions used drops to 116 and 117 for the periods 1980-1996 and 1990-96 respectively.

In Table 1 we present the estimated values of ρ and the associated p-values of a likelihood ratio test of the null hypothesis that $\rho = 0$ derived from estimating equation [1b]. The results show a clear pattern: the null hypothesis that $\rho = 0$ is strongly rejected in the simplest model, model I, for all the data sets except one; but in those models in which other variables, notably country dummies, are included in the *X* matrix, the null cannot be rejected in any case except one at the 10% significance level.[9] By contrast, likelihood ratio tests of the null hypothesis that the coefficients on the 10 country dummies were jointly zero in models III and V led to a rejection of the null at the 1% level in all the data sets. The rejection of the null in the simplest model clearly indicates the presence of clustering in European regional growth rates; the failure to reject that same null in any model which includes country dummies - and the high significance of the dummies themselves - suggests that this clustering is not due to geographic proximity itself but is because close regions tend to be in the same country.

Table 2 presents the results of estimating equation [1b] for the three redefinitions of the distance weights described in the previous section: in the first panel the weights are related to the absolute rather than relative distances between regions; in the second, the distance weights are dependent on the relative economic size of regions; and in the third the distance weights depend upon the relative standard of living of the regions. The main common feature of all the results is that, whereas in some of the models the value of ρ is positive and significant at 5%, this is not generally the case and, in all models in which country dummies

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1958; Denmark, Ireland and the UK who all joined in 1973; Greece who joined in 1981; Spain who joined in 1986; and Sweden who joined in 1995.

[8] It is conventional to include the initial level of income in the long-run growth equations to capture the idea predicted from standard growth models that economies with lower initial levels of income will grow faster. See Friedman (1992) for a criticism of this practice.

[9] We re-estimated each of the models shown in Tables 1-3 using the *square* of the inverse of the distance between regions. The results were not sufficiently different from those shown to make it worthwhile reporting them.

are included, the p-value associated with the test of the null hypothesis that $\rho = 0$ is well above 0.1, suggesting that geographic distance is insignificant. Once again likelihood ratio tests of the null hypothesis that the coefficients on the 10 country dummies were jointly zero led to a decisive rejection of the null in all data sets in all the models shown in Table 2.

Table 3 presents the estimated value of ρ and the associated p-value of a likelihood ratio test of the null hypothesis that $\rho = 0$ when geographic proximity is assumed to link regional growth rates in different ways from those we assumed in Table 1. In the top panel only systematic movements in other regions' growth rates have any influence; in the lower panel only innovations have any effect. The main feature of the results is that whereas in some of the simplest models ρ appears occasionally significant it is generally not so in models which include country dummies: in all such cases the p-values associated with the test of the null hypothesis that $\rho = 0$ are above 0.1. And again, in all cases, likelihood ratio tests suggested the country dummies themselves were highly significant.

We found the same broad pattern when we restricted our observations to the earliest 9 members of the EU or when we redefined the distance weights so that only regions within the same country were allowed to influence a region's growth rate - i.e. any proximity effect was assumed to stop at the border. In almost all cases the distance-weighted growth rate was only significantly positive if country dummies were absent whilst the country dummies themselves were highly significant. [10]

Finally it is worth noting that in none of the tables is there any obvious tendency for ρ to be of greater significance in the "later" data sets - sets B and D. Membership of the EU implies an absence of tariffs with other EU members; tariffs might act as a barrier preventing regions which are close but within different countries exerting an influence on each other; in the later period one might expect the role of geographic distance to have had more time to show itself. The absence of any such effect suggests again that the role of geographic distance in explaining clustering is a minor one.

4. Geographic proximity and the state of the cycle

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[10] Details of these and all other results mentioned but not presented here are available from the authors on request.

We now apply a similar methodology to shorter-term or cyclical movements in output, and thereby attempt to answer the question of whether the state of the cycle in a particular region is heavily influenced by the state of the cycle in nearby regions, and whether this influence appears to be due to geographic proximity or to membership of a particular country. For these results we redefine g_i as the deviation of the log of per capita output in region *i* from its trend. We use three measures of the trend in the log of per capita regional GDP: the first is the conventional linear trend derived from an OLS regression of the log of per capita output on time; the second and third are the Hodrick-Prescott (HP) filter (Hodrick and Prescott (1980)), and the Baxter-King (BK) Band-Pass filter (Baxter and King (1999)). The BK approach attempts to improve on the HP filter by additionally removing high-frequency components of the series and Baxter and King claim that it produces a reasonable approximation to the ideal filter which removes all but business cycle frequencies. Each of these three measures of trend output allows us to derive an observation on g_{it} for each of 135 regions drawn from 11 countries for each of the years 1981-1996.[11] In practice we found that our results were qualitatively unaffected by the choice of trend and so we report below only those results where g_{it} is based on the HP filter.[12]

In Table 4 we present the results of estimating, for each possible year, models which are special cases of the general model:

$$g_{it} = k + \beta_1 g_{it-1} + \rho \sum_{j=1}^{n} w_{ij} g_{jt} + \beta_2 \sum_{j=1}^{n} w_{ij} g_{jt-1} + \sum_{j=1}^{10} \beta_{2+j} cdum_j + \varepsilon_{it} \qquad [6a]$$

or

$$[I - \rho W] G_t = X\beta + \varepsilon \qquad [6b]$$

where $cdum_j$ is the zero/one country dummy for regions in country *j*.

In model I the *X* matrix contains only a constant; in model II it also includes the country specific zero/one dummies; in model III it contains a constant, the distance-weighted lagged deviations from trend of other regions, and the lagged deviation from trend of the region itself; in model IV it contains the elements of model III and the country dummies. Models III and IV capture the idea that the state of the cycle in any region may be influenced both by the

[11] The observations on regional output in Sweden were available only from 1985 and so were dropped for this set of results.
[12] The results of the other de-trending methods are available from the authors.

state of its own cycle in the previous period, and by the lagged state of the cycle in other regions. From the results presented in Table 4 a clear pattern emerges: the state of the business cycle is geographically clustered - the general significance of ρ in the simplest models demonstrates this - but, again, this clustering does not seem to be due to geographic proximity: for, once country dummies are included, in only two cases are the estimated values of ρ positive and significant at the 10% level.[13] On the other hand, likelihood ratio tests of the null hypothesis that the coefficients on the country dummies were jointly zero in models II and IV in Table 4 led to rejection of the null at the 1% level of significance in virtually every year.

This broad pattern was also apparent when we estimated a series of variants of [6b]. In Var1 we restricted the data set to include only the earliest 9 EU members; in Var2 we redefined the distance weights so that only regions within the same country were allowed to influence a region's growth rate; in Var3 the weights are related to the absolute rather than relative distances between regions, that is w_{ij} is defined simply as $1/d_{ij}$ for $i \neq j$; in Var4 and Var5 respectively region *i*'s weights reflect the ratio of region *j*'s and *i*'s output or per capita output as described in the previous section. In none of these cases did we find that our estimated values of ρ were consistently positive and significant at conventional levels of significance once country dummies were included. The country dummies themselves were highly significant in all cases. Rather than show all these results for each model we present in Table 5 only the estimated values of ρ and associated p-values for the most general version, model IV, of each of these variants. It is clear from these that there is apparently no consistent and significant influence for geographic proximity in explaining the clustering of cyclical movements in regional EU output once we condition on membership of a country.

The general picture emerging from these results is therefore similar to the picture that emerged from the previous analysis of long-run growth. On its own, geographic proximity appears to exert a strong and significant influence on the short-term behaviour of output: any region is more likely to be experiencing a cyclical boom, for example, if relatively close regions are experiencing one. But this significance seems to arise from the fact that regions

[13] We found a similar pattern when we allowed the distance weights to depend upon the square of the inverse of the distance between regions.

that are geographically close tend to be part of the same country: once allowance is made for this by the inclusion of country dummies, geographic proximity ceases to have a clear, significant and positive influence. [14]

5. *Conclusions*

Our results strongly suggest that, as measured by both the long-run and cyclical behaviour of output, the economic performance of the regions of certain EU countries is geographically clustered: if any particular region is experiencing a boom or has a high long-term growth rate it is more likely that the regions closer to it will also be experiencing a boom or have a high long-run growth rate. However, this appears to be not so much because regions are geographically close but because regions within the same country experience similar economic performance and that regions within the same country tend to be closer to each other than those that are not. Our findings then suggest that, at least at the level of EU regions, "cultural" rather than geographic distance is a key force inducing similarity of economic performance.

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[14] Clark and Wincoop (1999) find strong border effects on the state of the cycle across European regions but more evidence than we find of a statistically significant distance effect. They use a considerably smaller data set than we do and employ a different methodology which involves regressions of correlations of the state of the cycle across pairs of regions on (amongst other variables) measures of distance and country or border dummies.

Table 1 Long-Run Growth Rates

Estimates of ρ and associated p-values in the model $\left[I - \rho W\right]G = X\beta + \varepsilon$

	Data Set A		Data Set B		Data Set C		Data Set D	
Model	$\hat{\rho}$	p-val.	$\hat{\rho}$	p-val.	$\hat{\rho}$	p-val.	$\hat{\rho}$	p-val
I.	0.76	0.02	0.83	0.00	0.69	0.04	0.25	0.58
II.	0.12	0.81	0.77	0.01	0.13	0.78	0.33	0.45
III.	0.24	0.62	-0.90	0.11	0.23	0.62	-0.80	0.16
IV.					-0.05	0.91	-0.06	0.90
V.					-0.05	0.91	-0.82	0.15

Notes:

(i) Models:

Model I — X contains a constant

Model II — X contains a constant and the log of initial income

Model III — X contains a constant, the log of initial income and country dummies

Model IV — X contains a constant, the log of initial level of income, and the shares of agriculture and services in total output

Model V — X contains a constant, the log of initial level of income, the shares of agriculture and services in total output and country dummies

(ii) Data sets:

Set A. 1980-96; 142 regions from 12 countries

Set B. 1990-96: 146 regions from 12 countries

Set C. 1980-96: 116 regions from 12 countries

Set D. 1990-96: 117 regions from 12 countries

Table 2 Long-Run Growth Rates

Estimates of ρ and associated p-values in the model $[I-\rho W]G = X\beta + \varepsilon$

(i) Weights based on absolute rather than relative distance: $w_{ij} = 1/d_{ij}$; $j \neq i$

	Data Set A		Data Set B		Data Set C		Data Set D	
Model	$\hat{\rho}$	p-val	$\hat{\rho}$	p-val	$\hat{\rho}$	p-val	$\hat{\rho}$	p-val
I.	-0.90	0.02	0.80	0.35	-0.62	0.27	0.66	0.44
II.	0.13	0.75	1.44	0.08	0.29	0.57	1.20	0.17
III.	-0.29	0.69	-1.88	0.18	0.58	0.55	-0.79	0.61
IV.					-0.03	0.96	0.64	0.46
V.					1.03	0.21	-0.64	0.67

(ii) Weights for region *i* based on inverse of distance multiplied by the ratio of region *j*'s to region *i*'s output: $w_{ij} = \frac{(1/z_{ij})}{\sum_{j=1}^{n} 1/z_{ij}}$ where $z_{ij} = (1/d_{ij})y_j / y_i$ for $i \neq j$; y_j is region *j*'s GDP

	Data Set A		Data Set B		Data Set C		Data Set D	
Model	$\hat{\rho}$	p-val	$\hat{\rho}$	p-val	$\hat{\rho}$	p-val	$\hat{\rho}$	p-val
I.	0.68	0.04	0.86	0.00	0.59	0.13	0.22	0.66
II.	0.33	0.45	0.81	0.00	0.30	0.52	0.24	0.63
III.	0.37	0.45	0.10	0.83	0.28	0.57	-0.01	0.98
IV.					0.21	0.65	0.12	0.81
V.					0.16	0.74	0.04	0.94

(iii) Weights for region *i* based on inverse of distance multiplied by the ratio of region *j*'s to region *i*'s per capita GDP

	Data Set A		Data Set B		Data Set C		Data Set D	
Model	$\hat{\rho}$	p-val	$\hat{\rho}$	p-val	$\hat{\rho}$	p-val	$\hat{\rho}$	p-val
I.	0.38	0.16	0.84	0.00	0.35	0.20	0.26	0.57
II.	0.26	0.53	0.78	0.01	0.20	0.59	0.30	0.50
III.	0.36	0.39	-0.70	0.22	0.31	0.42	-0.63	0.27
IV.					-0.00	1.00	-0.06	0.91
V.					0.19	0.61	-0.65	0.25

Notes: See Table 1

Table 3 Long-Run Growth Rates

(i) Estimates of ρ and associated p-values in the model $G = [I - \rho W] X\beta + \varepsilon$;

	Data Set A		Data Set B		Data Set C		Data Set D	
Model	$\hat{\rho}$	p-val.	$\hat{\rho}$	p-val.	$\hat{\rho}$	p-val.	$\hat{\rho}$	p-val
I.	0.05	0.49	0.28	0.08	0.05	0.54	0.08	0.73
II.	0.72	0.06	0.26	0.67	0.75	0.04	0.42	0.50
III.	0.57	0.21	0.22	0.74	0.63	0.14	0.30	0.62
IV.					0.49	0.33	-0.45	0.54
V.					0.40	0.50	0.11	0.88

(ii) Estimates of ρ and associated p-values in the model $G = X\beta + [I - \rho W]\varepsilon$;

	Data Set A		Data Set B		Data Set C		Data Set D	
Model	$\hat{\rho}$	p-val.	$\hat{\rho}$	p-val.	$\hat{\rho}$	p-val.	$\hat{\rho}$	p-val
I.	0.10	0.34	0.31	0.06	0.10	0.40	0.12	0.67
II.	-0.71	0.10	-0.80	0.02	-0.69	0.09	-0.30	0.39
III.	-0.77	0.12	0.30	0.50	-0.74	0.11	0.44	0.28
IV.					-0.32	0.50	0.19	0.64
V.					-0.66	0.22	0.48	0.24

Notes: See Table 1

Table 4 Cyclical Movements in Output: Basic Model

Estimates of ρ and associated p-values in the model $[I - \rho W]G = X\beta + \varepsilon$

	Trend Based on HP Filter							
	Model I		Model II		Model III		Model IV	
	$\hat{\rho}$	p-val.	$\hat{\rho}$	p-val.	$\hat{\rho}$	p-val.	$\hat{\rho}$	p-val
Year								
1982	0.83	0.00	-1.88	0.01	0.69	0.00	-1.71	0.00
1983	0.68	0.06	0.21	0.71	0.69	0.03	-0.19	0.01
1984	0.35	0.43	-1.33	0.07	0.32	0.44	-1.45	0.05
1985	0.72	0.02	-0.30	0.60	0.40	0.02	0.03	0.81
1986	0.92	0.00	-1.03	0.07	0.66	0.00	-1.38	0.04
1987	0.92	0.00	-0.06	0.91	0.85	0.00	0.31	0.13
1988	0.95	0.00	0.59	0.12	0.95	0.00	-0.03	0.00
1989	0.93	0.00	0.23	0.64	0.25	0.07	-1.29	0.05
1990	0.79	0.01	-1.07	0.08	0.88	0.00	-0.72	0.03
1991	0.95	0.00	0.22	0.60	0.89	0.00	0.32	0.45
1992	0.95	0.00	0.08	0.87	0.86	0.00	-0.46	0.16
1993	0.78	0.01	0.63	0.12	0.66	0.03	0.48	0.03
1994	-0.17	0.76	-1.52	0.03	-0.10	0.00	-1.53	0.02
1995	0.91	0.00	0.46	0.30	0.85	0.00	0.20	0.02
1996	0.93	0.00	-0.46	0.38	0.76	0.00	-1.34	0.02

Notes:

Model I. X contains a constant;

Model II. X contains a constant and country dummies;

Model III. X contains a constant, the lagged dependent variable, and the distance-weights times the lagged value of G;

Model IV. X contains a constant, the lagged dependent variable; the distance-weights times the lagged value of G; and country dummies.

Table 5 Cyclical Movements in Output: Variants of Model IV

Estimates of ρ and associated p-values in the model:

$$g_{it} = k + \beta_1 g_{it-1} + \rho \sum_{j=1}^{n} w_{ij} g_{jt} + \beta_2 \sum_{j=1}^{n} w_{ij} g_{jt-1} + \sum_{j=1}^{10} \beta_{2+j} cdum_j + \varepsilon_{it}$$

	Var1		Var2		Var3		Var4		Var5	
	$\hat{\rho}$	p-val	$\hat{\rho}$	p-val	$\hat{\rho}$	p-val	$\hat{\rho}$	p-val	$\hat{\rho}$	p-val
Year										
1982	-0.20	0.242	-0.34	0.172	-3.41	0.005	-0.23	0.682	-1.07	0.009
1983	0.61	0.118	0.02	0.483	0.27	0.004	0.49	0.022	0.18	0.109
1984	-1.48	0.018	-1.00	0.000	-4.45	0.050	-0.56	0.222	-1.09	0.059
1985	0.36	0.487	0.02	0.754	0.73	0.689	0.13	0.572	0.12	0.833
1986	-0.41	0.531	-0.75	0.003	-3.06	0.133	-0.56	0.366	1.03	0.127
1987	0.69	0.002	0.03	0.026	1.50	0.050	0.24	0.373	0.29	0.087
1988	-0.19	0.021	-0.43	0.000	1.86	0.017	-0.26	0.034	-0.52	0.008
1989	-1.56	0.039	-1.03	0.002	-0.04	0.099	-0.19	0.686	-0.81	0.277
1990	-0.45	0.103	-0.41	0.022	0.03	0.494	-0.26	0.243	-0.57	0.023
1991	0.14	0.326	-0.00	0.869	0.21	0.318	0.24	0.000	0.25	0.545
1992	-0.35	0.222	-0.58	0.044	-0.25	0.373	-0.08	0.344	-0.46	0.175
1993	0.57	0.020	-0.28	0.001	2.69	0.000	0.55	0.102	0.53	0.008
1994	-1.30	0.059	-0.77	0.009	-2.71	0.207	-0.65	0.097	-1.31	0.070
1995	-0.41	0.006	-0.04	0.027	-0.55	0.108	0.55	0.044	-0.14	0.015
1996	-1.42	0.015	-0.71	0.002	-4.04	0.044	-1.05	0.100	-1.40	0.003

Notes:

Var1 Restricts data set to earliest nine members of EU

Var2 Restricts proximity effects to operate only within national borders

Var3 Defines weights in terms of absolute rather than relative distances

Var4 Incorporates the ratio of region *j*'s output to *i*'s output in the calculation of the distance weights

Var5 Incorporates the ratio of region *j*'s per capita output to *i*'s output in the calculation of the distance weights

References

Armstrong, H.W. (1991) "Regional problems and policies" in Crafts, N.F.R. & Woodward, N. (eds.) *The British Economy Since 1945* (Oxford: Oxford University Press).

Armstrong, H.W. & Vickerman, R.W. (eds.) (1995) *Convergence and Divergence Among European Regions* (London: Pion Ltd.)

Anselin, Luc. (1988) *Spatial Econometrics: Methodology and Models*. The Netherlands: Kluwer Academic Publishers.

Baxter, M. and R.G. King (1999) "Measuring business cycles: approximate band-pass filters for economic time series" *Review of Economics and Statistics*, 81(4) pp. 575-593

Benabou, R. (1996) "Heterogeneity, stratification and growth: macroeconomic implications of community structure and school finance" *American Economic Review*, 86 (3) pp. 584-609

Chatterji, M. and Dewhurst, J.H.L. (1996) "Convergence clubs and relative performance in Great Britain: 1977–1991" *Regional Studies*, 30(1) pp. 31–40.

Cheshire, P. and Carbonaro, G. (1995) "Convergence – divergence in regional growth rates: an empty black box" in Armstrong, H.W. & Vickerman, R.W. (eds.) *Convergence and Divergence Among European Regions* (London: Pion Ltd.)

Clark, T.E. and E. van Wincoop (1999) "Borders and Business Cycles" *Federal Reserve Bank of Kansas City Research Working Paper* August 1999.

Critz, J.M. (1995) "Economic growth and regional economic disequilibria in twentieth century Spain" *Research in Economic History*, 15, pp.71–98.

Engel, C. and Rogers J.H. (1996) "How wide is the border?" *American Economic Review*, 86(5) pp.1112–1125.

Friedman, M. (1992) "Do old fallacies ever die?" *Journal of Economic Literature*, 30, 2129-2132.

GAUSS. (1994) Aptech Systems Inc., Maple Valley, WA.

Gertler, M.S. (1995) "'Being there': proximity, organisation, and culture in the development and adoption of advanced manufacturing technologies" *Economic Geography*, 71(1) pp. 1-26.

Hodrick, R.J. and E.C. Prescott (1980) "Post-war US business cycles: an empirical investigation" Carnegie Mellon University manuscript.

Krugman, P.R. (1991a) "Increasing returns and economic geography" *Journal of Political Economy*, 99(3) pp.483–499.

Krugman, P.R. (1991b) "History and industry location: the case of the manufacturing belt" *American Economic Review Papers and Proceedings*, 81, pp. 80-83.

Lucas R.E. (1988) "On the mechanics of economic development" *Journal of Monetary Economics*, 22, pp. 3-42.

Lundvall, B-A. (1988) “Innovation as an interactive process: from user-product interaction to the national system of innovation” in *Technical change and economic theory*, eds. G. Dosi, C. Freeman, R. Nelson, G. Silverberg and L. Soete, 349-69. London: Frances Pinter.

Moreno, R. and Trehan, B. (1997) “Location and the growth of nations” *Journal of Economic Growth*, 2, 399-418.

Regional Studies (1999) June 1999 33(4) Special Issue: Regional Networking, Collective learning and Innovation in High Technology SMEs in Europe”.

Quah, D. (1996) “Regional convergence clusters across Europe” *CEPR* DP 1286

Storper, M. (1993) “Regional ‘worlds’ of production: learning and innovation in the technology districts of France, Italy and the USA” *Regional Studies* 27(5) pp. 433-55.

Data Appendix

1. Economic variables

Data on GDP and sectoral value added shares were obtained from the Eurostat data set at rcade at the University if Durham. GDP in constant 1990 ECUs were computed as follows: define nominal GDP in millions of ECU as $P_t y_t E_t$ where P is the price of output in units of the domestic currency, y is real GDP valued in constant 1990 units of the domestic currency, and E is the current ECU/Domestic currency exchange rate (price of one ECU in units of the domestic currency). So $\frac{GDP\ in\ current\ ECUs}{GDP\ \ in\ constant\ 1990\ domestic\ prices} = \frac{P_t y_t E_t}{y_t} = P_t E_t$

We assume that the price deflator for each region j is the same as the country's deflator. So, for region j:

$$\frac{1}{E_{1990}}\left\{\frac{P_t y_t E_t}{P_t E_t}\right\} = \frac{y_{jt}}{E_{1990}} \text{ is GDP in constant 1990 ECUs.}$$

Example: for the UK region "North" the Eurostat data base records GDP of 38,559 million ECU in 1995. The national GDP for 1995 is given as 859,746.2 million ECU or £600,015 million valued in 1990 prices. We estimate $P_{t_t} E_t$ (for 1995) as the ratio (859746.2/600015)=1.43288. GDP in constant 1990 ECUs is computed as

$$\left\{\frac{1}{0.713851}\right\}\left\{\frac{38559}{1.43288}\right\} = 37697.28152 \text{ ECU.}$$

For our tests we compute the long-run growth rates in real GDP between 1980 and 1996, and between 1990 and 1996. Subject to some minor qualifications noted below there are data available on 142 regions for the period 1980-1996, and for 146 regions for the period 1990-1996. Data were available for the following countries:

Country	**Maximum Number of Regions**	**Country**	**Maximum Number of Regions**
Belgium	11	Italy	20
Germany	31	Luxembourg	1
Denmark	1	Ireland	1
Greece	13	Netherlands	12
Spain	17	Sweden	6
France	22	UK	11

For a small number of regions in the smaller data set the initial level of income was not 1980. These were:

Region (Code)	Initial Year	Region (Code)	Initial Year
Corse (fr83)	1982	Noord-Brabant (nl41)	1981
Groningen (nl11)	1981	Limburg (nl42)	1981
Friesland (nl12)	1981	Stockholm (se01)	1985
Drenthe (nl13)	1981	Oestra Mellan. (se02)	1985
Utrecht (nl31)	1981	Sydsverige (se04)	1985
Noord-Holland (nl32)	1981	Norra Mellans. (se06)	1985
Zuid-Holland (nl33)	1981	Mellersta Norr. (se07)	1985
Zeeland (nl34)	1981	Oevre Norrland (se08)	1985

In the larger data set the initial level of income for Berlin (de3) was for 1991 not 1990.

2. Population data

Data on population were also obtained from the Eurostat data set at rcade at the University of Durham. There were a small number of gaps in the population series which, rather than lose observations, we dealt with as follows:

Population data on all French regions begin in 1982; for two regions of the Netherlands (nl21 Overijssel and nl22 Gelderland) population figures were only available from 1987 and for nl23 Flevoland from 1986. Population for the North and North West of the UK were only available from 1988. For each of these regions, *national* population growth rates were applied to the missing years. Finally, the population of the South East of England was derived residually (national population less the sum of the other regions) because the required detail was not provided in the Eurostat data base.

3. Distances

Calculation of distances between regions requires the specification of the "centre" of each region. In general this was the major or capital city of the area, occasionally the geographic centre. The longitude and latitude of the selected city or point were then derived from Philip's World Atlas (Reference Edition) 1996, Chancellor Press, London.

A listing of the regions used and all the other data are available from the authors on request.