European ‘Regional Clubs’: Do They Exist, and Where Are They Heading? On Economic and Technological Differences Between European Regions

By

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1. Introduction: Technological change in regions

Economists have always identified technological change as the prime factor behind economic growth. There are, however, clear differences between different ways in which economists from different theoretical perspectives have looked at the way in which technological change ‘works’. In traditional growth theory (Solow, 1956, 1970), technology is supplied as an exogenous public good. Countries, regions or firms are seen as entities, which, at least in the long run, can all make use of the same technology. Not surprisingly, the prediction of this theory is that growth paths of different countries or regions will (unconditionally) converge to each other.

In the recent so-called ‘new growth theory’, technology becomes a partly private and partly public good. For example, in Romer (1990), technological inventions can be patented by firms, which gives them the exclusive right to produce new (intermediate) goods, but, at the same time, inventions generate new ‘general knowledge’, which is freely available to all firms. This approach typically leads to ‘endogenization’ of steady state growth rates of countries, and, hence, convergence becomes ‘conditional’ on the factors endogenously determining this growth rate.

In the view of a group of economists identifying themselves as ‘Schumpeterians’ (e.g., Dosi, 1988), technological change is characterized by strong tendencies for cumulativeness, implying that not all firms (or countries, or regions) are equally well placed to make innovations. In this view, the innovation capability of firms depends on a number of tangible assets, such as knowledge embodied in people, experience with certain production processes, etc. A number of authors in this tradition (e.g., Fagerberg, 1987, Dosi, Pavitt and Soete, 1990, Nelson and Winter, 1982), have implemented this view of technology in theories of the relation between technological progress and economic change. They argue that technology is a strong disequilibrating factor in processes of economic growth, giving rise to the opportunity of pervasive growth rate differentials between countries.

In economic geography, a similar argument about technological change is found. This body of work stresses the importance of local spillovers in technology. For example, research and development (R&D) is more efficiently carried out when other R&D-intensive firms or institutions (public research labs, universities) are close by, because this enables the R&D firm to draw on resources such as skilled personnel, and to interact with other R&D-performers. Examples of this line of research are Cowan and Cowan (1997) and Jaffe, Trajtenberg and Henderson (1993).

Spatial technology spillovers combined with cumulative innovation capabilities of firms may easily lead to self-reinforcing, virtuous circle type processes of economic growth. Thus, a (small) initial advantage of one region in terms of innovation capabilities would generate a higher growth rate in this region, as well as attract new R&D-performing firms to the region. This would in turn lead to higher growth, etc. If there are, however, at some stage also some ‘negative feedback’ effects, such as congestion, decreasing marginal returns to (R&D) investment, or increasing (real) wages, such a process of diverging growth rates is likely to come to a stop at some level, leading to a positive and persistent growth rate differential between regions.[1]

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[1] Dixon and Thirlwall (1975) provide an example of a model which has these characteristics. The model does not have, however, endogenous R&D investment, but relies on the Kaldor-Verdoorn law for

On the other hand, however, the idea of technology as something that may be imitated is not entirely strange. Obviously, once an innovation has been made, there is a certain potential for other firms (or regions, or countries) than the original innovator to imitate it. What is crucially stressed, however, in the above mentioned ‘Schumpeterian’ theories, is that this imitation process requires some learning capability as well as investment in ‘learning’ from the side of the imitator. Thus, for imitation, a firm needs capabilities, just as it needs capabilities for innovation. Obviously, the two capability sets differ: an innovator needs to be on the technological frontier, while an imitator can afford to be a little behind, but needs a strong absorptive capacity. From the point of view of a region or country, both types of capabilities are crucially related to institutions such as the education system (see, e.g., Abramovitz, 1994).

What is the driving force for this paper is not so much the consequences that this perspective on technology and economic change has for individual regions. Instead, the idea is that spatial technology spillovers may also extend over regional borders. In other words, the basic hypothesis in this paper is that technology spillovers between regions have a strong spatial component. This implies that on the map of European regions considered here, one may, for example, find ‘clusters’ of high-growth regions engaged in high-tech activities, while other, economically more backward ‘clusters’ are relatively blank with respect to technology. The basic aim in this paper is to explore whether one can usefully identify such clusters, as well as to explore the consequences thereof for differences in economic performance between regions.

The idea of such ‘regional clubs’ in Europe is not only a theoretical one stemming from the above observations about the nature of technology. Commonly used phrases such as ‘Europe at different speeds’ indicate the general concern among policy-makers and ‘policy-watchers’ for increased heterogeneity from an economic point of view, which may bring with it a decreasing tendency for ‘social cohesion’. An important element of European regional policy is indeed to enhance such social cohesion. The so-called ‘structural funds’ are one well-known example of a policy instrument geared at reducing the economic ‘backwardness’ of the European regions ‘at lower speed’ or in ‘lower order growth clubs’.

In previous papers (Fagerberg and Verspagen, 1996, Fagerberg, Verspagen and Caniëls, 1997), the hypothesis of different ‘regional clubs’ in Europe was investigated applying regression analysis. Fagerberg and Verspagen (1996) identified three such growth clubs, which could (endogenously) be identified by unemployment rates, while Fagerberg, Verspagen and Caniëls (1997) used four ‘quartiles’ of (initial) GDP per capita. The emphasis in those papers was on explaining economic growth in regions, and the analysis of ‘clubs’ was limited to the attempt to come up with a number of ‘stylized’ explanations for differences in regional growth performance. The current paper, in a sense, takes the possibility of ‘regional clubs’ much more serious, and recognizes it as a natural outcome of the cumulativeness and the local character of technological change, and its relation to economic growth.

In exploring the existence of ‘regional clubs’, the analysis is deliberately started from two different types of clubs. The first type of clubs is defined from a purely economic perspective. Here, variables such as GDP per capita and its growth, (un)employment and productivity are looked at.

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productivity increases.

The second type is defined in terms of technology variables, and defines regional clubs as clusters of regions which differ in terms of investment in technology, as well as specialization in different production technologies. Obviously, the theoretical perspective sketched above points out that there would be some connection between the two types of clubs. One would, for example, expect that high-tech regions (those which are specialized in new technologies, and invest heavily in it) show relatively ‘good’ economic performance.

At the same time, however, it is clear that such a connection between the two types of clubs is far from simple or ‘linear’. Technological investment takes many different forms (see for example the distinction between innovators and imitators, as introduced above). It is likely that these different forms have different consequences for different economic variables. For example, in Fagerberg, Caniëls and Verspagen (1997), it was confirmed that regions with relatively low GDP per capita are relatively well-placed to grow rapidly due to imitation and ‘catch-up’, but they are not so well placed to perform R&D. A strong correlation between R&D-intensity and the level of GDP per capita was found, and, at the same time, an inverse correlation between initial GDP per capita and its growth rate. It is also true that growth may result from other than technological sources, such as natural resources and factor-intensive growth (rapidly growing population, inward migration, or high investment rates). When technology is embodied in people or investment goods, technology-intensive growth and factor-intensive growth are obviously interrelated.

In order not to equate technological performance and economic performance from the start, the analysis therefore proceeds by investigating the existence of regional clubs in Europe for each of the two types of clubs identified (economic and technological). After discussing the results for both types of clubs, the two different types of clubs will be combined, thus investigating the complex linkages between technology and economic performance in Europe in an explorative way.

2. The dynamics of Economic Growth, Productivity and Employment in European Regions during the 1980s

It is a well-known fact that European regions show widely varying economic performance. Table 1 shows some of the differences with regard to some of the most commonly used statistics to evaluate regional economic performance, for the sample of regions in France, Germany, Italy, Spain and the United Kingdom. Of the three variables expressed as levels (GDP per capita, productivity and the unemployment rate), unemployment is perhaps the one with the most ‘uneven’ distribution. This is indicated by the coefficient of variation (standard deviation divided by the mean), as well as positive skewness. For unemployment, the coefficient of variation is higher than for either (labour) productivity or GDP per capita, and this variable also shows a (positively) skewed distribution (the other variables do not show any particularly skewed distribution, the standard errors of the skewness statistic are relatively large). The large coefficient of variation points to heterogeneity between regions. Positive skewness indicates that the unemployment observations that can be characterized as ‘extreme’, tend to be larger than the mean. In other words, it indicates that the distribution for unemployment rates tends to have outliers with high unemployment.

Table 1. Differences in economic performance between European regions (France, Germany, Italy, Spain, United Kingdom), 1980s

Variable	Mean	STD	CV	Skewness	SE Skewness	N
Employment growth (%, annual)	0.94	0.99	1.05	0.64	0.28	75
Labour force growth (%, annual)	1.07	0.90	0.84	0.39	0.28	74
Productivity growth (%, annual)	1.98	0.62	0.31	-0.29	0.28	74
GDP per capita growth (% annual)	2.07	0.69	0.33	0.37	0.28	74
Unemployment rate (% 1983)	10.30	4.35	0.42	0.75	0.28	75
GDP per capita (ECU PPS, 1980)	11.36	2.62	0.23	0.10	0.28	74
Productivity (ECU PPS, 1981)	29.85	4.37	0.15	0.03	0.28	74

Source: calculations on the basis of the REGIO database of EUROSTAT.

Labour productivity shows a lower coefficient of variation than GDP per capita. Naturally, this is connected to the distribution of unemployment. In the regions with high unemployment, relatively fewer workers are engaged in the production of GDP, so that the unevenness of unemployment rates leads to higher disparity in GDP per capita.

In the case of growth rates, unevenness is generally larger than for the level variables. The coefficients of variation for the growth rates of employment and the labour force are larger than any level variable, productivity and GDP per capita growth rates show larger coefficients of variation than their level counterparts. The rate of growth of employment is somewhat smaller than the rate of growth of the labour force, illustrating the tendency towards higher unemployment rates in European regions over the 1980s. Employment growth shows positive skewness, as did the rate of unemployment, the other growth rates do not show skewed distributions.

Thus, European regions are generally more heterogenous from a dynamic perspective, than they were from a static perspective in the early 1980s. On itself, this conclusion does not imply any specific tendency for divergence or convergence in variables such as GDP per capita or labour productivity. This paper does not present additional evidence on trends with regard to convergence or divergence, but it has been well established that over the 1980s, contrary to the period before that, there was little 'net' convergence in terms of GDP per capita. For example, Fagerberg, Verspagen and Caniëls (1997) showed that although the 'poor' regions in the sample had the potential to grow faster due to 'catching-up opportunity', this was almost completely offset by differences in variables such as R&D efforts in the 'richer' regions. The net result was that the 'poor' regions grow a few tenths of percentage-points faster over the decade, but this has little effect on the differences in levels.

In order to explore the existence of regional clubs, cluster analysis is applied to the data on regional economic performance. Relative to the earlier approaches in Fagerberg and Verspagen (1996) and Fagerberg, Verspagen and Caniëls (1997), this approach has the advantage that the grouping is based on more than just one variable. Rather than the usual 'hierarchical clustering', an iterative procedure to establish the clusters is used.[2] This has the advantage that a wider range of clusters may be achieved. Contrary to hierarchical clustering, however, the number of clusters needs to be determined *ex ante* rather than *ex post*. It was arbitrarily decided to use four clusters, although the analysis was also carried out for three clusters. Given that the procedure points to significant differences between the four clusters (*p*-values smaller than 1% for all variables), these results are used. Clustering was done using the standardized values of all variables (so called *Z*-scores, obtained by subtracting the mean and dividing by the standard deviation).

Table 2a. Economic clusters of regions in Europe

	Clusters			
	1 (n=13)	2 (n=5)	3 (n=24)	4 (n=31)
GDP per capita, 1980	8.71	9.87	9.97	13.67
Productivity, 1981	25.21	31.40	27.23	33.55
Unemployment, 1983	15.35	14.60	11.05	7.23
Growth of GDP per capita	2.76	2.74	1.86	1.82
Growth of productivity	2.52	1.10	2.12	1.75
Growth of employment	2.03	2.71	0.47	0.59
Growth of labour force	2.17	1.55	1.08	0.52
In percentages of Cluster 4				
GDP per capita, 1980	64	72	73	100
Productivity, 1981	75	94	81	100
Unemployment, 1983	212	202	153	100
Growth of GDP per capita	151	151	102	100
Growth of productivity	144	63	121	100
Growth of employment	347	464	81	100
Growth of labour force	415	296	206	100

Table 2b. Statistically significant differences between the economic clusters

	1	2	3
2	*Y, GY*		
3	*GQ, GE, GN, UE*	*GQ, GY, GE, Y*	
4	all	*GQ, GE, GN, Q, UE*	*Q, Y, UE, GN*

Note: *Q* = GDP per capita (1980), *Y* = productivity (1981), *UE* = unemployment rate (1983), *GQ* = average annual growth of *Q* (1980-1990), *GY* = average annual growth of *Y*, *GE* = average annual growth rate of employment (1983-1990), *GN* = average annual growth rate of labour force (1983-1990).

[2] The K-means cluster analysis algorithm in SPSS 6.0 for OSF/1 is used. This algorithm requires the user to specify the number of clusters, and starts with a random cluster configuration. In the iterative procedure, cases are re-assigned to clusters on the basis of their distance to cluster centers.

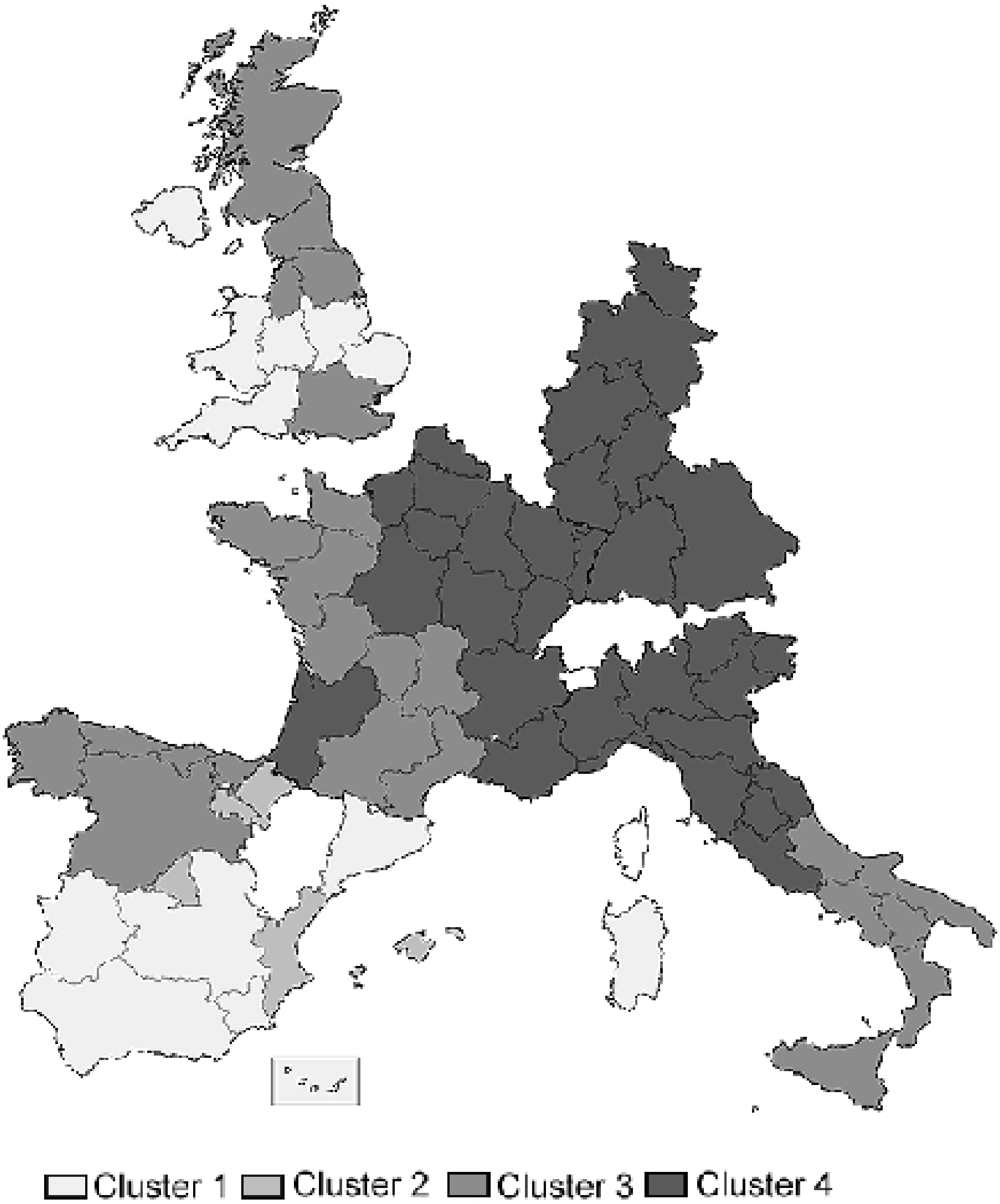

Figure 1. Economic clusters of regions in Europe

Table 2a gives the means for each of the economic performance variables for the four clusters, while Table 2b describes the results of Scheffe-tests for differences with respect to each of the variables between the clusters. What the latter table shows first of all, is that each cluster differs from all the others with respect to at least two variables. In other words, grouping two clusters together would indeed mean information is lost. Figure 1 shows the geographical distribution of the clusters.

In terms of GDP per capita, the clusters 1 through 3 do not differ significantly from each other. They are all relatively poor compared to Cluster 4: the values of GDP per capita in 1980 in Clusters 1 -3 are 64-73% of the value in Cluster 4. The 'rich' fourth cluster consists of 31 regions, located in three countries: seven German regions (i.e., the whole of Germany), thirteen French regions, and eleven Italian regions. They are all contingent, with the exception of one French region (Aquitaine). Within France and Italy, the 'rich' regions form clear geographical groups corresponding to well-known patterns: North-Italy and Central-North-East France. The analysis thus clearly seems to confirm the idea that for the economically advanced cluster, there is some spatial dimension to an explanation of its emergence. This cluster is characterized by low or intermediate growth rates of GDP per capita and productivity. Unemployment is well below the other clusters. Employment growth is also relatively low, but this is combined with low growth of the labour force, thus not leading to major dynamics in the unemployment rate.

There are several differences between the three 'poor clusters'. First of all, they differ in terms of countries. Cluster 1 is mainly Spanish and British (six regions each, plus one Italian region). Cluster 2, a small one, is exclusively Spanish, with 5 regions. Cluster 3 is a 'mixed bag' of five Spanish regions, six Italian, eight French regions and five British regions. In economic terms, the five Spanish regions in Cluster 2 are characterized by much higher productivity combined with relatively high unemployment. Cluster 1 is the one which is most economically depressed, with low GDP per capita and productivity, and high unemployment. GDP per capita and productivity grow relatively rapidly though, which indicates some tendency for catching-up. Cluster 3 has the lowest unemployment of the three 'poor' clusters, but it also shows the lowest growth rate of GDP per capita.

Overall, these results point out that there is indeed a core-periphery distinction among European regions. The core consists of Germany, North Italy, and the Central-North-East French regions that connect them. The 'periphery' consists of three separate groups, which can all in some way be characterized as 'depressed', although they show some significant differences between them. The 'peripheral' regions in Italy and France all belong to the most advanced part of the 'periphery' together with regions in Britain and Spain.

In terms of the spatial alignment of Clusters 1, 2 and 3, they do not form clear homogenous groups in the sense that they are contingent. It rather seems to be the case that in each country, the regions in Clusters 1 and 3 are contingent. Thus, while Cluster 4, the economically advanced one, seems to stretch over country borders into one big area around the Alps[3], the more backward

[3] One may indeed argue that Swiss regions, which are not taken into account in the analysis, are also a part of this cluster. Because there are no data available on Switzerland, however, this is a speculative argument.

clusters are confined to national borders. Within each country they are by and large contingent, indicating some degree of 'spatial auto-correlation', but this does not extend over international borders. These results generally confirm that the earlier results obtained by Fagerberg and Verspagen (1996) and Fagerberg, Verspagen and Caniëls (1997) are rather robust to changes in the variables used to group regions. There are, however, two important differences in the characterization of the clubs relative to these earlier papers.

First, there seems to be a clear spatial component in the clusters identified here. The economically advanced cluster extends over international borders into one big central EU area, the more backward clusters are confined to contingent geographical space within countries. Second, although there are differences in terms of economic growth between regional clusters, the differences in terms of level variables such as GDP per capita, productivity and unemployment rates remain rather substantial, and, thus, important. Although the 'poor clusters' grow somewhat more rapidly than richer regions, this difference is rather small. For example, based on the annual growth rates in Table 2a, it would take Cluster 1 about 50 years to catch up to the GDP per capita level of Cluster 4. For Cluster 2 and 3, respectively, this value is 36 and 781 years. It thus seems as if the phrases 'Europe at different speeds' or 'European growth clubs' are perhaps better replaced by alternatives such as 'Europe at different unemployment levels' or 'European GDP per capita clubs'.

3. Technology in European Regions during the 1980s

Technological change is a phenomenon that can only be measured in an indirect way. Economists often use either research and development (R&D, either expenditures on, or personnel engaged in R&D), or patent counts. R&D is clearly an input indicator, and as such it does not take into account differences in research-efficiency between regions. Patent counts are an indicator of technology output, but one with a number of shortcomings. For example, many patents do not lead to innovations, and of those that do, the economic impact may differ widely. Moreover, the efficiency of patents as a means of protection against imitation differs between sectors, which leads to different propensities to patent between sectors (this is, for example, high in pharmaceuticals, and low in aerospace). Part of the drawbacks of using patents as technology indicators can be overcome by using them in relative measures, such as the revealed technology advantage indicator, which will be introduced below. A final note that concerns both R&D and patents as technology indicators is that they do not work well for the non-manufacturing industries. For example, in many parts of the services industry, innovation is related to the introduction of new electronic equipment, and the use of this equipment in new products.

A solution for the shortcomings of R&D and patents as innovation indicators cannot be offered here. Until recently, data on R&D personnel was the only available source of information on comparative technological efforts in European regions. These data are not broken down by industry, and they are only available for a limited time span from the mid 1980s onwards. Breschi (1995) introduces patents as a regional indicator of technology, while Caniëls (1997) further extends Breschi's analysis by adding information on patenting by industries to the existing data. This paper uses the data developed by Caniëls (1997). This patenting data set is developed from information on patent applications at the European Patent Office (EPO). The main 'technology class' of each patent application is used to assign it to one or more of 22 industries within manufacturing, according to the concordance scheme developed by Verspagen *et al.* (1994). The patent applications are assigned to regions using a concordance scheme between postal codes and NUTS-regions, kindly supplied by EUROSTAT. The postal code of the inventor(s) is used for this purpose.[4]

The patent data are used as an indicator for technological specialization. Although information on 22 industrial classes is available, the choice was made to aggregate the data into three broad classes, i.e., 'high-tech' industries, 'medium-tech' industries and 'low-tech' industries. The classification of the 22 sectors into these groups is the standard one used by OECD, and is based on average R&D intensity of the sectors. High tech consists of pharmaceuticals (ISIC 3522), computers and office machinery (ISIC 3825), electronics (ISIC 3832), aerospace (ISIC 3845) and instruments (ISIC 385). Medium tech industries are chemicals (ISIC 351+352-3522), machinery (ISIC 382-3825), electricals (ISIC 383-3832), automobiles (ISIC 3843) and other transport (incl. high speed trains, ISIC 384-3841-3843-3845). All other industries are classified as low-tech. The main reason for aggregating the data into these three groups is that the number of patent applications in some of the regions is quite small. This would yield very small, or even zero numbers in many of the detailed sectors. Although this problem is not completely solved in the case of the three aggregate sectoral groups, it is certainly less severe in most cases.

The data on high-tech, medium-tech and low-tech patenting is used to calculate the so-called revealed technological advantage (RTA) index, which is defined as the share of the sectoral group in total patenting of the region divided by the share of the sectoral group in total patenting of all regions. Values higher than one point to specialization of the region in that specific sectoral group, values between zero and one point to 'negative specialization'. In order to make the index symmetric, however, a transformation of the type $(X-1)/(X+1)$, where X is the revealed technology advantage index, is applied. This new indicator always lies in the interval $[-1,1]$, with positive (negative) values pointing to specialization (despecialization).

Although these different technology indicators have different shortcomings, and are aimed to measure different aspects of the 'technological system' of a region, strong cross-regional correlations between the variables were found. For example, R&D-intensity is strongly positively correlated with high-tech specialization (RTA). This correlation points to the fact that regions which are strong in high-tech also tend to invest more in technology. The reason for this is that the technological opportunities in their production processes are higher.

Table 3 gives summary statistics on the technology variables. The general impression from the table is that disparity between regions in terms of technology is higher than in terms of the economic variables considered earlier. The coefficient of variation for each of the technology variables is higher than for any variable in Table 1, and each of the distributions of the technology variables is skewed. For R&D intensity (interpreted as measuring differences in 'absolute' technological efforts), heterogeneity as measured by the coefficient of variation is lower than for

[4] One could also have used the postal code of the applicant, but this may introduce a bias to the more 'central' regions, because patents are often applied for by the main offices of firms, rather than the research facility. The patent's inventors are always 'natural persons', listed by their living address. However, given the possibility that inventors live in 'neighbouring regions' to their workplace, this introduces another possible distortion, but this seems less serious than in the case of using applicants' addresses, especially given that the regions are relatively large.

the three specialization variables, with medium-tech specialization coming out as the indicator with most heterogeneity.[5]

Table 3. Differences in technological performance between European regions (France, Germany, Italy, Spain, United Kingdom), 1980s

Variable	Mean	STD	CV	Skewness	SE Skewness	N
R&D intensity, 1985	0.42	0.47	1.12	1.93	0.28	73
High tech specialization	-0.13	0.25	-1.92	-1.53	0.28	73
Medium tech specialization	-0.05	0.15	-3.00	-2.34	0.28	73
Low tech specialization	0.10	0.18	1.80	-1.23	0.28	73

Source: calculations on the regional patenting database at MERIT, developed by Caniëls (1997) and the REGIO database of EUROSTAT.

The means of the high-tech and medium-tech specialization variables are both negative, while the one for low-tech specialization is positive. By definition, however, the weighted average of these variables over regions (using the volume of patenting as weights) is zero. The non-zero means are the direct result of the uneven distribution of patenting over regions. There is only a limited number of regions (24, or about one third of all regions) with strong patenting profiles in high-tech. These regions show up with a positive specialization index for high-tech, but the majority of regions has a negative value for this indicator. The same holds, but to a lesser extent, for medium-tech patenting. Skewness for all three RTA variables is negative. This indicates that the extreme observations tend to be negative, or, in other words, that extreme specialization patterns tend to be characterized by absence of patenting in one of the three sectors, rather than by patenting in only one of the three.

The analysis proceeds by applying the same type of cluster analysis as in the case of the economic variables. However, because the number of patents on which the technology specialization variables are based is rather small in some of the regions, it was decided to enter only regions with more than 50 patents into the cluster analysis. The RTA variables for regions with less than 50 patents are considered as less reliable, because a (random) change of one or a few patents would have large consequences for the values of these variables. The 17 regions for which the number of patents is smaller than 50 were assigned to one cluster *ex ante*, i.e., without any statistical analysis. The remaining regions were classified into three clusters using the same procedure as before.

The analysis points to significant differences between clusters, as in the case of economic variables (Table 4b). The differences in terms of technology specialization seem to be somewhat more pronounced than in terms of mere R&D intensity, however. Only the two clusters with extreme R&D intensity (i.e., highest and lowest) differ significantly from each other in terms of R&D

[5] It should be noted that, of course, by their nature, the specialization variables measure dissimilarity instead of similarity. One would therefore expect some degree of heterogeneity between regions with regard to these indicators. Technological heterogeneity between regions is thus better illustrated using coefficients of variation in the 'absolute' indicators. Nevertheless, the statistics for the specialization indicators have some informational value, especially those for skewness.

intensity. With regard to high-tech specialization, all three clusters are different from each other.

As Table 4a shows, the cluster which was *ex ante* fixed on the basis of patent counts, also shows the lowest R&D intensity. Among the three other clusters, there is clearly one which can be characterized as 'high-tech'. This cluster shows a high value for R&D intensity and positive technology specialization in high-tech industries. Figure 2 shows the geographical spread of the technological clusters.

Table 4a. Technological Clusters of Regions in Europe

	1 (n=17)	2 (n=14)	3 (n=24)	4 (n=17)
R&D intensity	0.05	0.26	0.53	0.78
High tech specialization		-0.31	-0.14	0.09
Medium tech specialization		-0.02	0.04	-0.07
Low tech specialization		0.23	0.06	-0.03
In percentages of Cluster 4				
R&D intensity	6	33	68	100

Table 4b. Statistically significant differences between the technological clusters

	2	3
3	*HT, LT, MT*	
4	*R&D, HT, LT*	*HT, LT, MT*

Note: *R* = business R&D employment as a % of the labour force (1985), *P* = number of patent applications per manufacturing employee, *P* = number of patent applications per employee, *LT* = specialization in low-tech, *MT* = specialization in medium-tech, *HT* = specialization in high-tech.

Cluster 4, the 'high-tech' cluster of Europe, has R&D-intensity about 17 (Cluster 1), 3 (Cluster 2) or 1.5 (Cluster 3) times larger than the other clusters. Cluster 4 is thus a technologically advanced cluster. It has 17 members, which is not a very small or large group, compared to the other clusters. Germany (4), France (5) and the United Kingdom (5) are the main countries represented in this cluster. Together, these regions are specialized in high-tech, although not to an extreme degree.

In geographical terms, there is some evidence for the regions of Cluster 4 to clutter together in space, but this applies within countries rather than over international borders. The degree of clustering is certainly less than was the case for the economically advanced cluster. A possible explanation for this difference is the hypothesis that technological spillovers take two different forms. First, they may have an effect on the efficiency of the R&D process itself, thus leading to geographic cluttering of regions with high R&D-intensity (but the evidence presented here is not very conclusive on this). Second, technology spillovers may lead to economic effects, in the sense that regions adjacent to R&D-intensive regions grow rapidly, without necessarily having high R&D-intensity themselves. The interpretation of the spread of the clusters over the map of Europe would then be that the first type of spillovers is more 'local' than the second, leading to high-tech clusters of regions within each country, and a broad contingent cluster of economically advanced regions encompassing and connecting the high-tech clusters across international borders.

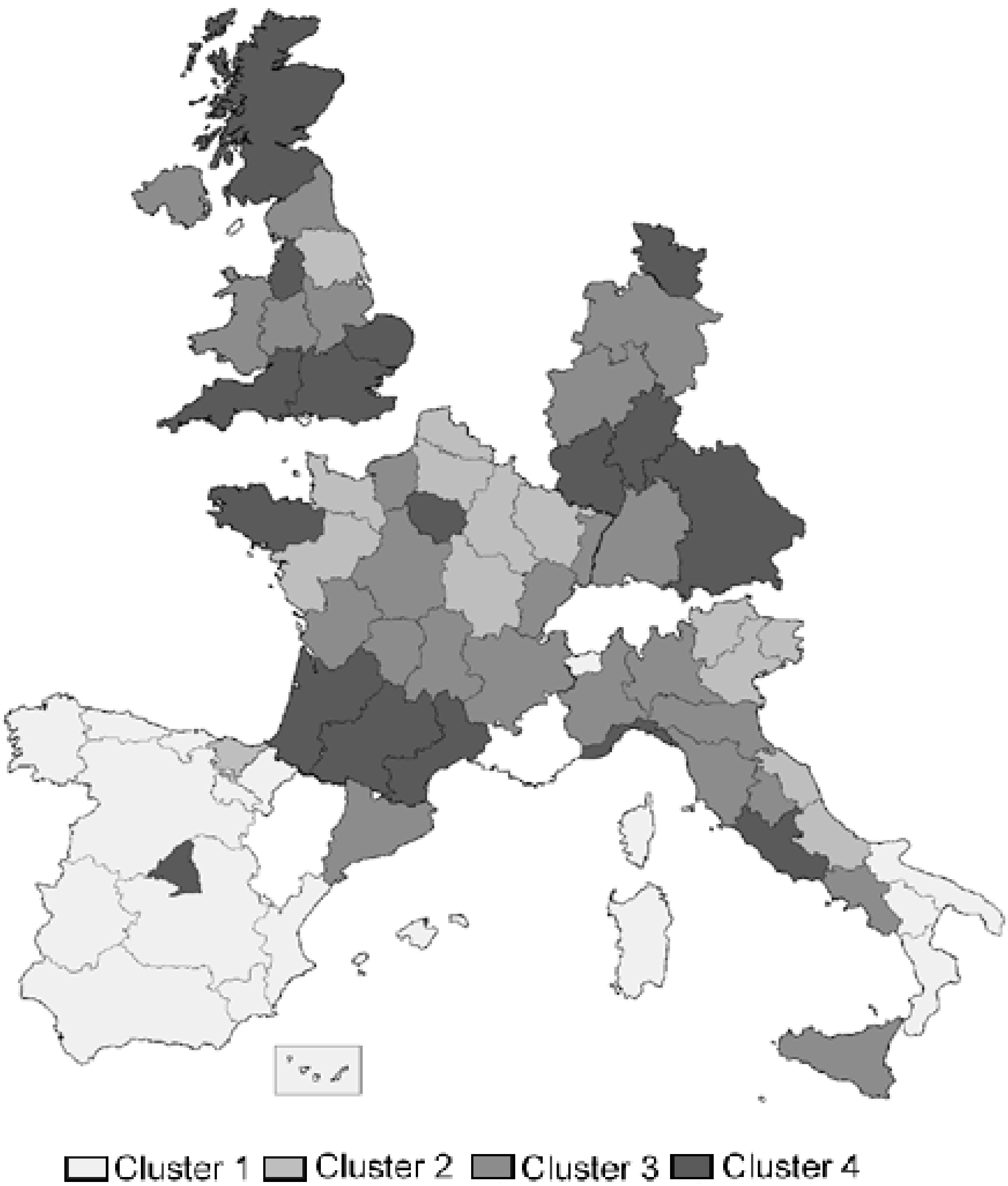

Figure 2. Technology clusters of regions in Europe

Cluster 3 is a relatively large cluster (24 members). It is specialized in medium- and low-tech industries, and has second-ranking R&D intensity. This cluster consists of a mixed bag of nationalities: French (8), Italian (7), and British regions (5) regions, German (3) and one Spanish.

Cluster 2 consists mainly of French (7) and Italian (5) regions. This cluster shows specialization in low-tech industries, with a neutral value for medium-tech specialization, and a negative value for high-tech specialization. Finally, Cluster 1 (fixed *ex ante*) consists mainly of Spanish and Italian regions. The mean of R&D-intensity is very low in this cluster. No specialization values are given for this cluster because of the small number of patents.

Summarizing, as was the case with economic variables, one can usefully distinguish between different clusters of European regions with regard to technology efforts. There are 14 regions forming a 'high-tech core' in this respect. It thus turns out that the 'technological core' of Europe is smaller than the 'economic core'.

4. Combining economic and technological cluster membership

Finally, membership of the four economic and technological clusters is confronted with each other. Table 5 gives the 'crosstab' of both memberships. Reasoning from a 'linear' relationship between economic performance and technology, one might expect a tendency for the observations to clutter around the diagonal of the table. However, as was already stressed in the introduction, this is too simplistic, and one should not expect a 'perfect association' between the two cluster dimensions.

Table 5. Combining economic and technological cluster membership

	Technology Clusters				
Economic Clusters	1	2	3	4	
1	6	0	5	2	13
2	4	0	0	1	5
3	7	5	6	6	24
4	0	9	13	8	30
	17	14	24	17	72

In terms of the distinction core-periphery, it is not so clear that being a core technology region increases the probability of being a core economic region. The probability to be a core economic region given that the region belongs to the technology core, is 47%. For a region not being part of the technology core, this probability is only 44%. The other way around, there seems to be a somewhat stronger connection. The probability for a core technology region to be in the most backward economic cluster is only 11%, while for regions not belonging to the technology core, this probability is 20%.

However, for the non-technology core regions, the probability of being a core economic region differs strongly between the three peripheral clusters. For Technology Cluster 3, the probability of being a core economic region is 54%, for Technology Cluster 2, it is 64%. However, for technology Cluster 1, the probability is zero. Although this does not say anything about causality, it is clear that being technologically backward does have economic implications.

What are the reasons for this rather fuzzy relation between technology and economic performance? First, there is the geographical factor, as already outlined above in the discussion of differences in geographical constellations of the economically and technologically advanced regions. Many of the regions in Technology Clusters 2 and 3 (with relatively high probability to be part of the economic core), are located closely to technological core regions. Thus, although their own technological capabilities are low, they may benefit from technology spillovers from the nearby high-tech regions.

The second reason for the higher probability of Technology Clusters 2 and 3 to be part of the economic core might lie in the technology dynamics of the regions themselves (contrary to the previous argument, which was based on spillovers). These regions are characterized by technological specialization in low-tech or medium-tech industries, and a negative value for high-tech specialization. These industries may benefit from catch-up driven growth, rather than depend on (own) R&D efforts.

5. Conclusions: perspectives on European cohesion

This paper has shown that, during the 1980s, different European 'regional clubs' exist. In terms of variables measuring economic performance, it was found that Europe (Germany, France, Italy, Spain, the United Kingdom) can be characterized as consisting of four regional clubs. One of these is clearly the advanced club, with high productivity, GDP per capita, and relatively low unemployment. The other three clubs are less advanced, although they all have some specific characteristic that distinguishes them from the other two 'peripheral' clubs. In the technology dimension, one advanced club with high R&D intensity, and patenting in high-tech activities was found. The other three 'technology clubs' are gradually less R&D-intensive, and specialize more in the low- and medium-tech industries.

Comparing the geographical constellations of the advanced technology and economic clusters, several interesting points emerge. First, the advanced technological cluster is smaller in terms of the number of regions than the advanced economic cluster. Second, whereas the advanced economic cluster is an almost perfectly contingent set of regions stretching from Germany, through Central and East France to Northern Italy, the advanced technological cluster is a set of centers within individual countries, but is not geographically connected across borders.

What do these results have to say on the issue of economic policy aiming to stimulate economic development in the regions which are members of the 'peripheral' clusters (among others the 'less favoured regions', in eurospeak)? One might interpret the results here as saying that innovation and technology are successful factors in getting on to the road to economic development, but this obviously raises the important and difficult question of how to stimulate innovation in regions which are relatively backward from the economic perspective. Innovation requires resources not easily available in those backward regions, such as investment by firms, public research institutes and universities. In other words, many of the 'less favoured regions' are caught in a virtual circle of low innovation and low productivity / GDP per capita. Simply subsidizing (private or public) research in those regions would not solve the problem because one cannot develop (high-) technology from scratch.

The results here do point to another policy option, however. The fact that the economically advanced cluster is very much broader than the technologically advanced cluster, as well as the specific geographical arrangement found, points to the interpretation that 'high-tech' regions have a rather broad spillover in terms of economic growth. Thus, regions adjacent to 'high-tech' regions may not directly benefit in terms of attracting more R&D-intensive firms, but they may have important benefits in terms of higher economic growth. One may think of simple (Keynesian) multiplier effects as one causal factor explaining such a pattern.

From the policy point of view, this would mean that one would not necessarily have to concentrate on the less favoured regions themselves when implementing technology policy to stimulate development. Instead, policy makers might target one or a few central region(s), in which facilities such as public research institutes or universities would already be relatively abundant. Complementary policy measures might then focus at facilitating economic spillovers from this central region targeted for technological development to the regions around it. One might for example think about stimulating business contacts between the central and peripheral regions.

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Appendix. Regions used in the analysis

NUTS	NAME
DE1	Baden-Wurttemberg
DE2	Bayern
DE7	Hessen
DE9+DE5	Niedersachsen + Bremen
DEA	Nordrhein-Westfalen
DEB+DEC	Rheinland-Pfalz + Saarland
DEF+DE6	Schleswig-Holstein + Hamburg
UK1	North
UK2	Yorkshire and Humberside
UK3	East Midlands
UK4	East Anglia
UK5	South East
UK6	South West
UK7	West Midlands
UK8	North West
UK9	Wales
UKA	Scotland
UKB	Northern Ireland
IT11	Piemonte
IT12	Valle d'Aosta
IT13	Liguria
IT2	Lombardia
IT31	Trentino-Alto-Adige
IT32	Veneto
IT33	Friuli-Venezia Giulia
IT4	Emilia-Romagna
IT51	Toscana
IT52	Umbria
IT53	Marche

IT6	Lazio
IT7	Abruzzo-Molise
IT8	Campania
IT91	Puglia
IT92	Bascilicata
IT93	Calabria
ITA	Sicilia
ITB	Sardegna
FR1	Ile de France
FR21	Champagne-Ardenne
FR22	Picardie
FR23	Haute-Normandie
FR24	Centre
FR25	Basse-Normandie
FR26	Bourgogne
FR3	Nord- Pas-de-Calais
FR41	Lorraine
FR42	Alsace
FR43	Franche-Comte
FR51	Pays de la Loire
FR52	Bretagne
FR53	Poitou-Charentes
FR61	Aquitaine
FR62	Midi-Pyrenees
FR63	Limousin
FR71	Rhone-Alpes
FR72	Auvergne
FR81	Languedoc-Roussillon
FR82	Provence-Alpes-Cote d'Azur
FR83	Corse
ES11	Galicia
ES12	Principado de Asturias
ES13	Cantabria
ES21	Pais Vasco
ES22	Communidad Foral de Navarra
ES23	La Rioja
ES3	Communidad de Madrid
ES41	Castilla y Leon
ES42	Castilla -la Mancha
ES43	Extremadura

ES51	Cataluna
ES52	Comunidad Valenciana
ES53	Islas Baleares
ES61	Andalucia
ES62	Region de Murcia
ES7	Canarias