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by

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# TWIN –PEAKS IN E.U. REGIONAL PRODUCTIVITY DYNAMICS: a nonparametric analysis

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**Abstract:** Working within the 'distributional approach', this research offers evidence, based on empirical density estimates and modality tests, of past polarization in regional labour productivity in EU-15. Most importantly, it provides evidence on the related ergodic density which suggests that this polarization may persist in the future. This past and probably future polarization is primarily related to the service sector of the regional economies and not to manufacturing industries sector.

**Keywords:** regional labour productivity, EU, distributional analysis, nonparametric methods, stochastic processes.

**J.E.L. codes**: D39, O18, C14.

## 1. Introduction

The aim of the paper is to analyze regional productivity dynamics in the European Union (EU-15) over the 1980 to 2000 period. The empirical evidence that has been accumulated so far on this issue is surprisingly limited. To facilitate its aims this analysis relies on a continuous state-space, discrete-time, stochastic process approach first introduced in the subject matter by Quah (1997). The present research, however, differs from its predecessors in that it additionally employs a non-parametric method, originally suggested by Trede (1998), for addressing mobility, but most importantly, it further estimates the ergodic density following more recent developments in the literature advanced by Johnson (2000, 2005). The ergodic density is a long-run, statistical in nature, equilibrium. It shows the shape of distribution that will exist if past dynamics continue operating unchanged in the future.

The main finding of this research is that this long-run equilibrium is a twin-peaks one. This bimodality in labour productivity might not come as a surprise if past realizations of its regional distribution are also examined. With the help of a visual inspection of kernel density estimates at several points in time, but also, most importantly, with the indispensable help of modality tests, evidence is offered that the distribution of regional labour productivity in the EU-15 was multimodal throughout the study period.

As further evidence obtained suggests, most future (in terms of ergodic density) and past multimodality in EU regional labour-productivity is attributable to polarization effects in market services and non-market services sectors, but not to manufacturing industries. A crude distinction of these groupings in tradable and non-tradable sectors, along with the theoretical implications of such a distinction, may help in offering a possible explanation for these results. Overall, it appears that service-sectors markets are by far less integrated within the E. U. when compared to manufacturing industries.

The paper is organized as follows: the next section discusses the motivation of this research along with key relative results of previous research. In section three an account of the methodology and data used is provided. The penultimate section presents and discusses the results obtained and in the last section some conclusions are drawn.

## 2. Motivation and review of empirical evidence

As Lopez-Bazo et al. (1999) rightfully note, despite the fact that growth models make predictions regarding convergence in productivity, which can be then transformed in terms of output per capita, most existing studies have tested the convergence hypothesis using the closely related to output-labour input ratio, but not identical to it, output per capita.

Three concepts of convergence have dominated most of the existing literature. Namely, these are $\beta$ (beta) convergence, conditional $\beta$ convergence and $\sigma$ (sigma) convergence. The notion of $\beta$ convergence is directly derived from the neoclassical growth model (Solow, 1956) and owes its name to its testable equation form. In a nonlinear least squares framework the latter becomes (Barro and Sala-i-Martin, 1995, p. 386):

$$\log\left( y_{it} \big/ y_{it-T} \right) \tfrac{1}{\mathrm{T}} = a - \log\left(y_{it-T}\right) \cdot \left(1 - e^{-\beta \mathrm{T}}\right) \tfrac{1}{\mathrm{T}} + \varepsilon_{it}$$

where y is the variable of interest observed in points of time that are T periods apart and $i$ stands for cross-sectional units of observation (countries, regions). A $\hat{\beta} < 1$ is an indication of $\beta$ convergence in the sense that those regions that are further below a common steady state grow faster.

But does this imply that $\beta$ convergence would lead to a reduction over time of regional disparities? If a reduction of regional disparities is meant to be a reduction in the cross sectional standard deviation ($\sigma$ convergence), then the answer is: not necessarily so. Hart (1995) explains why $\beta < 1$ is a necessary but not sufficient condition for decrement in the variance of the variable of interest over time. In particular, since the variance of $y_i(t)$ is

$$V[y(t)] = \beta^2 V[y(t-\mathrm{T})] + \sigma^2$$

and it holds that $\rho^2 = \dfrac{\beta^2 V[y(t-\mathrm{T})]}{V[y(t)]}$ ,where ρ is the correlation between y(t) and y(t-T), it follows that: $V[y(t)]/V[y(t-\mathrm{T})] = \beta^2/\rho^2$ .

Since $\rho \leq 1$ , given the above relationship, an increasing variance when $\beta < 1$ can emerge only when $\rho < \beta < 1$. When β>1, the variance always increases. Thus, when $\beta < \rho < 1$ (see Hart, 1995, p. 291), the variance of the distribution does not need to be increasing with t.

The hypothesis made in the empirical analysis of convergence to a common steady-state has been heavily criticised (Quah, 1993, 1996a, 1996b) as it assumes convergence towards some representative economy. Some efforts have been made to account for differences in steady states (Mankiw et al 1992; Barro and Sala-i-Martin, 1991) by trying to purge the estimated β from influences that relate to differences in steady states and are proxied by some extra conditioning variables in the right hand side of the basic empirical formulation. Within this effort, variables have been used that relate to the possible effects of differences in the mix of economic activities (see Barro and Sala-i-Martin, 1995; Paci and Pigliaru, 1997; Martin, 2001), dummy variables that reflect geographical factors and policy instruments, and variables that account for differences in educational attainment as well as differences in the quality and potential of human capital. Galor (1996), however, suggests that both conditional *β-convergence* as well as polarization, or club convergence, (Durlauf and Johnson, 1995), may consistent with the neoclassical growth model.

The main motivation, however, for following the particular approach that will be presented in the next section, stems out from Quah's (1997) criticism to cross sectional and panel data regressions which aim to analyze economic growth and convergence. The point made is that these can capture the behaviour of a conditional average, but remain uninformative about both distribution (external shape) and intra-distribution dynamics. A reduction of the variance of a regional income distribution over time (σ convergence) may be informative for an overall lessening of inequalities, but it remains silent about features relating to intra-distribution mobility. That is, regions changing their relative positions in the distribution over time.

In addition to Quah's valid criticism, it may further be argued that some general features of the external shape distribution may persist despite some reduction in its overall variance. Let us say, for example, that instead of being unimodal, the distribution of the variable of interest is a mixture of two normal distributions with different means ($\mu_1, \mu_2$) and variances ($\sigma_1, \sigma_2$) and mixing proportions ($\pi_1, \pi_2$). Would the sole information of a reduction of its overall variance from a point in time to another then bear any information regarding the reasons for the distribution becoming unimodal from following its initial bimodality? The answer is again not necessarily so. The overall mean of the mixture at a point in time is given by $\mu = \pi_1\mu_1 + \pi_2\mu_2$ and its variance $\sigma^2 = \pi_1\sigma^2{}_1 + \pi_2\sigma^2{}_2 + \pi_1\pi_2(\mu_1 - \mu_2)^2$ (McLachlan and Basford ,1988 p.106). For $\Delta^2 > (27\sigma^2)/\{4(1+\lambda)\}$ , where $\Delta = \frac{|\mu_1 - \mu_2|}{\sigma}$ is the Mahalanobis distance and $\lambda = \frac{\sigma_2^2}{\sigma_1^2}$ (McLachlan and Peel, 2000, p.11), a value of $\pi_1$ exists for which the density is bimodal. Therefore, the bimodality of a mixture density depends on mixing proportions, proportions variances but, more importantly, on the distance between the proportions' means.

A number of studies (Quah, 1996b; Magrini, 1999; Lopez-Bazo et al., 1999; Le Gallo, 2004) have used discrete-state space discrete-time Markov chains to analyze regional economic dynamics in the E. U. in response to Quah's criticism to studies using the so called Barro-regresion. However, as far as the variables of interest are essentially continuous, discretization of the state-space may distort dynamics and even remove the Markovian property (Quah 1997; Bulli, 2001)[1]. Thus, as a result, the state that the process arrives in a forward step would depend not only on its immediate predecessor but also on others before that. Quah (1997) first used a stochastic kernel (or Markov transition function), an essentially a continuous state-space, discrete-time Markov process, in order to analyze the dynamics of relative GDP per capita in a sample of 105 countries in the 1960 to 1988 period. Magrini (2004, p. 2744) maintains that "…the distributional approach to convergence – particularly when based on nonparametric stochastic kernel estimations – appears to be generally more informative than convergence empirics within the regression approach, and therefore represents a more promising way forward". Magrini applies this technique to an analysis of relative GDP per capital dynamics in 110 EU-12 regions over the 1980 to 1995 period[2]. His results point to some considerable persistence of regional disparities. Moreover, when the same technique is applied to 122 functional urban regions (FURS, see Cheshire and Carbonaro, 1995) over the same period, the results reveal, apart from persistence, a twin-peaks property. In a recent paper that also uses alternatives to Barro-regressions methodological tools (Bayesian predictive density method), Canova (2004), using data on 144 NUTS II over the 1980 to 1992 period, finds that the steady-state distribution regional income data cluster around four poles. Using the

[1] Magrini (1999) avoids arbitrariness in discretising the state space by using some statistical criteria, whereas Bulli (2001) uses a Markov-Chain Monte-Carlo technique that provides a discrete state-space that preserves the Markovian property.

[2] Magrini (2004) uses the, REGIO (Eurostat) based, CRENOS database.

same study period but a sample of 129 regions, Lopez-Bazo et al. (1999) also detect some polarization in GDP per capita utilizing both snapshot kernel density estimates for 1980 and 1992 and discrete state space Markov processes. What is more interesting, within the context of this present research, is that these authors find that, in contrast to GDP per capita, there was no polarization in the distribution of GDP per worker in both distribution-snapshot terms and ergodic distribution derived from their Markov-chain application. Using panel data on 97 European regions for the 1981-1990 Cuadrado-Roura et al. (2000) find evidence for unconditional $\beta$ convergence in regional productivity (GVA/employment) that amounts to an annual speed of convergence of 2.8%-3.5%. Accounting for regional fixed-effects, the authors obtain an estimate of β about 17%. However, using also alternative methods of analysis, Cuadrado-Roura et al. (2000) carefully clarify that despite these trends towards $\beta$ convergence significant regional differences persist. In contrast, Martin (2001), using a cross-sectional growth regression on the EU-15 plus Norway regions, finds that the GVA per worker converged by less that 1% per annum during 1975-1986, at about a mere 0.4% for the period 1975-1998, whereas the convergence parameter obtained was not statistically different from zero for the period 1986-1998. Accounting for the hypothetical growth rate that each region would have according to its industry-mix, Martin obtained a statistically significant speed of *conditional –$\beta$* convergence of 0.9% p.a. only for the period 1975 to 1986.

Lopez-Bazo et al. (2004) use data on GDP per worker, a proxy of labour productivity, for 108 regions of the first EU-12 over the 1980 to 1996 period and account for spatial effects in their analysis of unconditional and *$\beta$ -convergence.* The authors obtain speeds of unconditional $\beta$- convergence from 2%-2.4% p.a. and an annual speed of convergence within the 2.7%-3% band for conditional $\beta$ convergence in their spatial externalities formulations. In formulations that account for residual spatial dependence, annual convergence rates of 2.8% and 5% for unconditional and conditional *β-convergence* respectively were obtained. On the other hand, Boldrin and Canova (2001) find weak evidence for *β-convergence* and *σ-convergence* in labour productivity in EU NUTS II regions over the same time period. Moreover, these authors point out that this amount of convergence makes little difference in changes in the overall distribution (see p. 236, p. 241).

Gardiner et al. (2004), using data on output per hour worked for 197 EU-15 regions over the period 1980 to 2001, find an annual speed of *β*-convergence of about 1%. On the novelty side of this research, *β*-convergence for both traded and non-traded sectors are also estimated. The authors include manufacturing, energy, business services and intermediate services in the traded sectors group, whereas the non-traded sectors group consists of construction, household services and public sector services. The speed of convergence for the traded sectors group was estimated to be about 0.8% p.a. whereas for non-traded sectors was somewhat higher at about 1.1%. p.a. This difference between traded and non-traded sectors is worth noting, despite that fact that both rates indicate very slow convergence in productivity. There are no other regional analysis results with which to contrast the above presented finding. There are, however, some related empirical results on the OECD cross-country level of analysis that are worth discussing along with their theoretical motivation.

According to Ben-David (1993), the connection between trade and per capita income convergence is primarily based on the factor price equalization theorem (FPE). Under certain assumptions (Samuelson, 1948, Samuelson, 1949), international trade will first lead to the equalization of tradable-goods prices across countries and consequently to a factor price equalization. Slaughter (1997) clarifies that the FPE theorem does not directly imply per capita income convergence since the latter also depends on factor quantities in addition to factor prices. It is argued that if endowments between countries are becoming dissimilar, incomes will diverge despite factor-price convergence. Two other ways in which, according to Slaughter (1997), international trade can affect per capita income are: a) through the mediation of international flows of technology from advanced to less advanced countries thus increasing marginal productivities and hence factor prices and income levels in the latter; and b) by increasing capital-labour ratios in less advanced countries through imports of capital goods. Ben-David (1993, 1996) offers some evidence that suggests that income convergence is higher between counties that trade extensively with one another. In particular, Ben-David (1993) provides some evidence suggesting that trade liberalization coincided with a higher per capita σ-convergence of the original six member countries of the European Economic Community (E. E. C).

Within the rationale presented above, the implied productivity convergence may be expected to be more direct and sizeable in manufacturing than in services since the former is highly tradable and the latter depends primarily on domestic (local demand).

Bernard and Jones (1996) study productivity convergence for 14 OECD countries, among them Belgium, Denmark, Finland, France, Italy, Netherlands, Sweden, UK and West Germany, over the 1970 to 1987 period. The major finding of this study was that convergence was strongly evident in the services sectors,[3] but weak or absent in the manufacturing sectors. The authors further scrutinized this, as they themselves acknowledge (p. 1234), surprising result of no convergence in manufacturing productivity. As this could be attributed to the use of workers as the measure of labour productivity instead of hours worked, the latter were also used in defining

[3] The services aggregate used in this study encompasses retail trade, transportation/communication, financial-investment, real estate services and other services. Government services were excluded.

productivity. These additional results showed some *σ-convergence* in manufacturing up to 1975 but not later. As a second test of robustness, the hypothesis that productivity levels in manufacturing had already converged by 1975 was checked. The authors provide, against this hypothesis, some evidence suggesting that substantial differences in productivity levels remained after 1975. Some newer evidence, provided by studies using somewhat different methodologies but also OECD countries data (Gouyette and Perelman, 1997; Carree et al. 2000), offers support to Bernard and Jones' (1996) main empirical finding.

These results, however, contrast those obtained by Dollar and Wolff (1993) suggesting considerable convergence among OECD countries within manufacturing over the 1963 to 1985 period. In Dollar and Wolff (1993), the primary measure of labour productivity used was value added per work hour and it is manufacturing that exhibits the smallest inter-country variation in labour productivity over the 1970 to 1985 period (pp. 92-98). This is attributed to the openness of the manufacturing sector to trade and investment (p.92). Using output per worker led to slightly weaker convergence, although the difference was not large when compared to convergence obtained for output per hour worked (p. 52 en 9). Trade openness has been the most significant factor leading to real wage convergence in a sample of sixteen OECD countries that contains among them ten EU member states, for the 1961 to 1984 period (Mokhtari and Rassekh, 1989).

Van Ark et al. (1999) provide some evidence suggesting that there are no indications that productivity gaps in selected service industries (transport and communications and retail trade and wholesale trade) are any smaller than in manufacturing industries. In addition, estimates of productivity in transport- communication and distribution suggest that productivity differentials between Canada, France, Germany, Netherlands and the US are at least as large as those in manufacturing.

### 3. Methodology and Data

Central to the methodological approach used here is the stochastic kernel (stochastic transition function). A working definition of the stochastic kernel follows.

If $X_t$ is a stochastic process and $X_t \sim \phi_t$ then, under conditions explained in Quah (1997)[4], $\phi_{t+\tau} = \int_E P^\tau(x, A)\phi_t dx$ where $E$ is a continuous state space such as $E \subseteq \Re$ and $A$ any subset of $E$. The stochastic transition function or stochastic kernel is a generalization of a Markov matrix such as $\Pr\left(X_{t+\tau} \in \mathrm{A} \middle| X_j, j \le t;\ X_t = x\right) = P^\tau\left(x, A\right)$.

The independence of $P^\tau$ on the values of $X_j, j \le t$ is the Markovian property (what happens in time $t$+$\tau$ depends only on $t$ and not on what was in times prior to $t$), whereas the independence of $P^\tau$ and $t$ is the time homogeneity property (the probability depends only on the length of the time step and not on where in time this step is taken).

The distribution of the variable of interest $v$ time intervals ahead of $t$ is then given by

$$\phi_{t+v\tau} = \int_E P^{v\tau}(x, A)\phi_t dx$$

A nonparametric estimate of the stochastic kernel is based on estimating $\hat{f}_\tau(y|x) = \dfrac{\hat{f}(y,x)}{\hat{f}(x)}$ where $y$ stands for $X_{t+\tau}$ and $x$ for $X_t$. A product Gaussian kernel was used to estimate the joint distribution:

[4] See also Meyn and Tweedie (1996) for stochastic processes with a general state space.

$$\hat{f}(x,y) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_x\sqrt{2\pi}}e^{-0.5\left(\frac{x-x_i}{h_x}\right)^2}\frac{1}{h_y\sqrt{2\pi}}e^{-0.5\left(\frac{y-y_i}{h_y}\right)^2}$$

where ( $h_x, h_y$) represent bandwidths calculated with the direct plug in method (Sheather and Jones, 1991) applied separately in each dimension.

To get an empirical estimation of the marginal pdf of x , the above formulation is integrated in respect to y : $\int \hat{f}(x,y)dy = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_x\sqrt{2\pi}}e^{-0.5\left(\frac{x-x_i}{h_x}\right)^2}\int_{-\infty}^{\infty}\frac{1}{h_y\sqrt{2\pi}}e^{-0.5\left(\frac{y-y_i}{h_y}\right)^2}dy$

Note however (Scott, 1992, p. 220, 125, 150) that:

$$\hat{f}(x) = \int_{-\infty}^{\infty}\hat{f}(x,y)dy = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_x\sqrt{2\pi}}e^{-0.5\left(\frac{x-x_i}{h_x}\right)^2}\int_{-\infty}^{\infty}\frac{1}{h_y\sqrt{2\pi}}e^{-0.5\left(\frac{y-y_i}{h_y}\right)^2}dy = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_x\sqrt{2\pi}}e^{-0.5\left(\frac{x_i-x}{h_x}\right)^2}$$

Since the stochastic kernel may be seen been as a transition matrix with a continuum of rows and columns, the relationship between two distributions over a time interval of length $\tau$ can written as: $f_{t+\tau}(y) = \int_{-\infty}^{\infty} f_\tau(y|x)f_t(x)dx$

The long-run (ergodic) distribution is then the solution (Johnson, 2000; 2005) to $f_\infty(y) = \int_{-\infty}^{\infty} f_\tau(y|x)f_\infty(x)dx$. Johnson (2005) develops an approach to obtain a solution (if it exists) to the above problem. If such a solution exists over an interval [a, b], then this interval can be partitioned in *n* non-overlapping subintervals and the conditional probabilities $f_\tau(z_j|x_i)$ can be estimated (let $z_{i,}x_j$ be midpoints of these intervals). If *n* is sufficiently large then $\sum_{j=1}^{n} f_\tau(z_j|x)\frac{b-a}{n} \approx 1$ for any $x \in [a,b]$ . If, next, $p_{ij} = f_\tau(z_j|x_i)\frac{b-a}{n} \geq 0$ are defined, this results in a $n \times n$ $\boldsymbol{P}$ matrix that has the same structure as a transition probabilities matrix with elements $p_{ij}$ such that for any *i,* $\{p_{ij}\}_{j=1}^{n}$ may be treated as conditional probability mass function. If the largest eigenvalue of this matrix is unity then the rescaled (unit sum) left eigenvector ($\psi$) corresponding to this eigenvalue has the property $\psi = P\psi$. The ergodic density can then be evaluated as $f_{\infty}(y) = \psi \Big/ \frac{b-a}{n}$.

A graphical device for assessing mobility, originally suggested by Trede (1998) in a somewhat different context, may supplement the stochastic kernel. This relies on non-parametrically estimated quantiles of the conditional cumulative distribution function. The conditional c.d.f. is estimated using the Nadaraya-Watson (see Pagan and Ullah 1999 p. 83) non-parametric regression estimator: $\hat{F}_{\tau}(y|x) = \dfrac{\sum_i K\left(\frac{y-y_i}{h_y}\right) R\left(\frac{x-x_i}{h_x}\right)}{\sum_i K\left(\frac{y-y_i}{h_y}\right)}$

where $R(z) = \int_{-\infty}^{z} K(u)du$ is the integrated kernel and $K(\cdot)$ is a Gaussian kernel.

To get the quantiles of $F_{\tau}(y|x) = E((Y_i \le y)|X_i = x)$, $\hat{F}_{\tau}(y|x)$ is numerically inverted to obtain $\hat{F}_{\tau}^{-1}(p|x)$ for selected $p$ values.

One might want to check the picture obtained by the implied dynamics against past realizations of the distribution. In this case, obtaining snapshots of the distribution of the variable of interest during various points in time in the past and visually assessing their different features may be of some help. However, this is essentially an empirical probability-density estimation exercise and it is well known that its result would crucially depend on the binwidth chosen (Jones et al., 1996). That is, if one very large binwidth is chosen, then the empirical density estimate obtained will tend to be oversmoothed, whereas the choice of a very small binwidth will, on the other hand, tend to produce a relatively curly curve. The crucial question, then, becomes how large is large when the chosen binwidth (*h*) is concerned. Silverman (1981) developed a bootstrap based test (see Efron and Tabshirani, 1993, pp. 230-234 for an excellent presentation of the test) in order to address this question and, thus, assess multimodality.[5] This test has been introduced in the economic convergence literature by Bianchi (1997). To test the null hypothesis that the number of modes is *k* ($H_0 : \#m = k$) against the alternative hypothesis of a number of modes larger than *k* ($H_a : \#m > k$) the test-procedure proceeds as follows (the presentation here follows Efron and Tabshirani, 1993):

Step 1: Since as *h* increases the number of modes in a Gaussian kernel is non-increasing, the smallest value of *h* consistent with *k* modes (*h critical*) should be first determined. A 'mode' is meant here to be a point on the empirical density estimate around which the tangent to the curve changes its slope from positive to negative. This can be determined using numerical derivatives of the empirical density estimate for each such binwidth candidate within a range of its possible values. Call this, consistent with *k* modes binwidth, $\hat{h}_k$.

Step 2: Draw *B* (a positive integer) samples such as $\zeta_1^*, \zeta_2^*, ..., \zeta_n^*$ each with replacement from $x_1, x_2, ..., x_n$ and consequently calculate:

$$x_i^* = \bar{\zeta}^* + \left(1 + h_k^2 / \hat{\sigma}^2\right)^{-1/2} \left(\zeta_i^* - \bar{\zeta}^* + \hat{h}_k \varepsilon_i\right), i = 1,2...,n$$

where $\bar{\zeta}^*$ is the mean from $\zeta_1^*, \zeta_2^*, ..., \zeta_n^*$, $\hat{\sigma}^2$ is an estimate of the data variance and $\varepsilon_i$ are standard normal variables. The factor $\left(1 + h_k^2 / \hat{\sigma}^2\right)^{-1/2}$ scales the estimate so that

[5] The reader should be aware that the p-values reported in Silverman (1981) are not correct and thus may want to check Silverman (1986, p.147).

its variance is approximately $\hat{\sigma}^2$. The procedure that refers to this step is called smooth bootstrapping since it essentially concerns sampling from a rescaled density estimate.

Step 3: This is essentially a shortcut to the test-procedure originally suggested and requires for each bootstrap sample to estimate the empirical density $\hat{f}^*\left(\cdot\,;\hat{h}_k\right)$ using $\hat{h}_k$. Next, count the number of bootstrap samples where the number of modes is larger than $k$ ($\#m > k$)

Step 4: The achieved significance level is $A\hat{S}L_{boot} = \frac{\#m > k}{B}$, that is the proportion of bootstrap samples with more than $k$ modes. The decision rule is: *fail to reject the null hypothesis of k modes whenever the* $A\hat{S}L_{boot}$ *is larger than some standard level of significance.*

This is not a nested test and its results should be interpreted as a hierarchical set of significance tests. That is, one should successively test for an increasing number of modes until a particular number of them is accepted (see Silverman, 1981, p. 99).

The study period (1980-2000) is partitioned so to provide five four-year transitions of 194 (mostly NUTS II) EU-15 regions[6]. All transitions are taken into account in order to derive the stochastic kernel. The variable of interest is regional gross value added (GVA in basic prices) per employee of each region in 1995 million € relative to contemporaneous data average. The data are taken from the Cambridge Econometrics European Regional Database (2004). A number of studies have used this database in a related research context (see for example Armstrong, 1995; Fingleton, 1997, 1999; Martin, 2001; Badinger et al., 2004; Gardiner et al. 2004). This database is based on

[6] See the Appendix for a list of the regions included in the analysis.

Eurostat's Regio database, the latter having been supplemented where gaps existed by national resources (Cambridge Econometrics, 2003).

As in Lopez-Bazo et al.'s (1999) study, the productivity measure used here is not expressed in purchasing power parities but in constant prices of a common currency. Thus, our productivity measure is, purposely, not purged from spatial price-level differentials as the latter partially reflect differences in productivity across regions[7]. Interregional differences in price levels within the E. U. may, to some extent, result from differences across member states. The so called Balassa-Samuelson model (Balassa, 1964; Samuelson, 1964; see also Rogoff, 1996) posits that the price level is positively correlated with GDP per capita across countries. In the Balassa-Samuelson model, differences in the price levels among countries are primarily determined by differences in the tradable-goods sector productivities. Those countries that are more productive in the tradable goods sector will have higher wages in this sector than lower productivity countries (in the same sector). However, within these higher-productivity countries, labour mobility between sectors will drive wages in the lower productivity non-tradable sector of the economy up to the wage level of the tradable sector. The opposite will be case within the countries of lower tradable-sector productivity. While, under certain conditions, arbitrage would erode whatever price differentials exist in tradable goods across countries, the prices of non-tradable products and services are primarily determined by local supply and demand conditions. As a result, differences in national income levels then explain to a great extent differences in price levels.

[7] Deviations from the "law of one price" may also be attributed to transport and distribution costs, imperfectly competitive product markets, market segmentation and differences to regulatory and fiscal systems (see European Economy, 2001, July)

According to the European Economy (2001), a 60% of differences in the price levels between member states can be explained by differences in per capita income levels, whereas De Grauwe and Skudelny (2002) review studies and also provide their own evidence that offers some support to the Balassa-Samuelson proposition in the case of 13 EU member states over the period 1971 to 1995. On the other hand, some evidence that is referred to by the European Central Bank (2002) seems to suggest a price level convergence both within E. U. and the Eurozone that was more pronounced in the late 1980s and early 1990s, especially in the tradable goods sectors, but that slowed down after that.

## 4. Results

The methodology described in the previous section is applied to produce results for the EU-15, primarily NUTS II, regions. First comes the estimation of the stochastic kernel for which Figure 1 below presents its graph. To better understand this graph, a fixed point can be chosen on axis labelled $X_t$ and, slicing the graph starting from this point and going parallel to $X_{t+4}$ axis, the estimated distribution of incomes conditional on this initial level can be traced. Such estimates are similar in concept to a row of a transition probability matrix since the estimated densities integrate to ones as rows in a transition probability matrix sum up to one. Thus, roughly speaking, these conditional probability density estimates describe transitions over a 4 year interval from a given income value in period t. As it can be seen the conditional density has several distinguished peaks.

_______________________Figure 1 ______________________________

Although helpful, the details of the above graph may still be difficult to understand. The comprehension of the implied dynamics is further assisted by the corresponding contour plot that follows. Figure 2 thus reveals that most of the major peaks for relative labour productivity lie mainly on the diagonal line of inertia. The concentration of probability mass on the diagonal implies that regions end where they began in relative productivity terms over a 4-year time horizon. This result accords with the persistence result found in Magrini (2004).

____________________________________Figure 2______________

Such an analysis, based primarily on contour plot commentary concerned with the location of its major peaks in relation to the diagonal, has been a standard practice in the relative literature (Quah, 1997; Johnson 2000; Magrini, 2004). There is a lot of detail in the contour plot, however, that is difficult to summarize. Non parametric quantiles of the conditional c. d. f. may be helpful in accomplishing this. The graphical device suggested by Trede (1998) and was discussed in the previous section better summarizes the information contained in a stochastic kernel by converting it into plain probabilistic, though cumulative, terms. In Figure 3, the results of estimating various quantiles of the conditional c. d. f. are graphed. The high degree of persistence demonstrated by the data used offers some unfavourable ground for demonstrating the potential of this device in such a research context. However, there are still some interesting features to note in the quantile graph.

__________________________Figure 3__________________________________

For example, regions having relative labour productivity levels of about 0.7 to 1.2 times that of the EU-15 regional sample indicates that the $0.5^{th}$ quantile curve almost coincides with the 45 degrees line of inertia. This means that 50% of regions having labor productivity that matches that of the average in the sample (1 in the horizontal axis) would not exceed their initial value over a 4-year time horizon. Only 10% of them would go lower than about 0.9 times the sample average, whereas an equal 10% would beyond 1.1 times the sample mean. However, from those regions initially having productivity 1.3 and 1.4 times the average productivity, only 30% of them would exceed their initial relative productivity level. Therefore, there is a group of regions having initial productivity above average that seems to recede over a four year interval. On the other hand, those regions with initial productivity of about 0.55 and 0.65 times that of the regional average, have a 50% chance to exceed relative productivity levels of 0.6 and 0.7 respectively. Thus, there is some limited evidence of mobility in some parts of the relative productivity distribution.

The nonparametric estimates of the conditional c. d. f. are directly derived from the stochastic kernel and help summarize its dynamics. However, analyzing only these conditional cumulative probabilities would be unacceptable in assessing the long-run stationary distribution as it would inadmissible to assess the ergodic distribution of a discrete state space Markov chain by simply looking at the entries of a transition probabilities matrix. In both cases, the long-run distribution requires a large number of iterations on the stochastic matrix or stochastic kernel applied on the initial distribution.

Johnson's (2000, 2005) approach has been applied in deriving the 'ergodic density' and the result of this exercise is graphed in Figure 4.

__________________Figure 4____________________________________

Such a sharp spatial productivity-divide across EU-15 is certainly a very bleak future prospect. It lacks all of the optimism some evidence produced by different approaches has kept alive regarding the future of regional disparities in the European Union.

But what about the past? What were the key features of the distribution of regional productivity across EU-15 in different points in time in the past? Some kernel empirical density estimates would help visualise such a view. In figure 5 below the empirical density estimates of relative regional productivity in 1980, 1985 and 1990 are presented.

Figure 5

A visual inspection of Figure 5 suggests that bi(multi)-modality was the case in all 1980, 1985 and 1990 distribution snap-shots. In Figure 6, one gets the same picture for 1995 and 2000.

Figure 6

As such, it seems that the ergodic distribution presented earlier as a long-run equilibrium distribution does not completely appear out of nowhere.

Is this bimodality, obtained from kernel density estimation exercises, a fact or fiction? The results obtained as explained in an earlier section on methodology crucially depend on the binwidth used. In this case, some modality tests are in order. In Table 1, the results of these modality tests using a 1000 each time bootstrap samples are presented.

Table 1

The test fails to accept the null hypothesis of unimodality in all years considered. Bimodality cannot be rejected in 1980, 1985, 1990 and 1995. If a 10% significance level is chosen, then bimodality is rejected in 2000 in favour of tri-modality which cannot be rejected. The bootstrap-based modality tests consequently support that multimodality was a rule rather than an exception in respect to regional productivity dynamics in Europe.

Without aspiring to provide with some hard answers about multimodality by delving into some thorough causal investigation, some additional analysis will explore some sectoral facets of the subject matter. In Figure 7, the ergodic density for manufacturing and energy sectors (ESA 95 sections C+D+E) is presented.

________________________Figure 7______________________________

The twin-peaks feature is not evident in this case. In Figure 8 and Figure 9 snap-shots of the distribution of interest are also provided for several points in time.

________________Figure 8_________________________________________

_____________________Figure 9_____________________________________

In all snapshots there is no such bimodality as that observed when total economy regional labour productivity was analyzed. However, there are some sizable bumps in 1985, 1995 and 2000. In Table 2 below, the results of the modality tests for manufacturing and energy sectors productivity are presented.

___________________________Table 2________________________________

Using a 10% level of significance, the null hypothesis of unimodality cannot be rejected in all years considered. Although inequalities exist in manufacturing productivity across regions, these appear to be less pronounced when compared with the twin-peaks situation of total-economy regional productivity.

Next comes the analysis to market services (wholesale and retail; hotel and restaurants; transport, storage and communication; financial intermediation; real estate, renting and business activities) sectors. In Figure 10, the ergodic density for market-services sectors is presented.

________________________________Figure 10_____________________

The twin-peaks feature returns in this case. Snapshot information is also provided in Figure 11 and Figure 12 that follow.

Figure 11

Figure 12

As in the case of all-sectors aggregates, the visual inspection the empirical density estimates for the market-services sectoral aggregate seem to suggest multimodality. Again the modality bootstrap-based test is helpful in providing additional evidence. In Table 3 the bimodality hypothesis fails to be rejected in 1980, 1995 and 2000. In contrast, unimodality is not rejected in 1990 and 1995.

Table 3

The evidence produced seems to indicate that the manufacturing (plus energy) sector is far more integrated than the market-services sectors with the E.U.-15. This might not be unrelated to the fact that manufacturing products are more tradable than services. Some similar evidence that is produced for non-market services[8], but is not presented here in order to save space, suggests that this sectoral grouping might be another place to look in trying to understand polarization in labour productivity across E. U. regions.

## 4. Conclusions

The aim of this research was to analyse regional labour-productivity dynamics within E.U.-15. Unlike most of its predecessors, this research uses neither Barro-regressions nor discrete state space Markov chains. Foremost, the distributional aspects of regional productivity are analysed using both static and dynamic approaches. The static analysis employs empirical (kernel) density estimation for obtaining snapshots of the distribution of interest in various points in time. Apart from visualisation of the related graphs, modality of the empirical densities has been assessed by using

[8] It is available on request by the author.

bootstrap-based tests. The dynamic analysis has used the stochastic kernel methodology. However, it has also enlarged the toolbox usually used in this research context, by deriving quantiles of the conditional c.d.f, and, most importantly, by deriving the 'ergodic density'. Thus, working further within the 'distributional approach', this research offers some evidence suggesting that polarization is, most probably, here to stay in E. U. regional labour productivity differentials. This polarization appears to be more related to the service sector of the economy than to manufacturing industries. This result calls for some measures to be taken in order to facilitate and further accelerate integration in the services sector within the E .U. The results obtained seem to vindicate concerns (Quah, 1996a,b) about the usefulness of, solely, relying on cross-section regression and single distribution moments in assessing economic dynamics.

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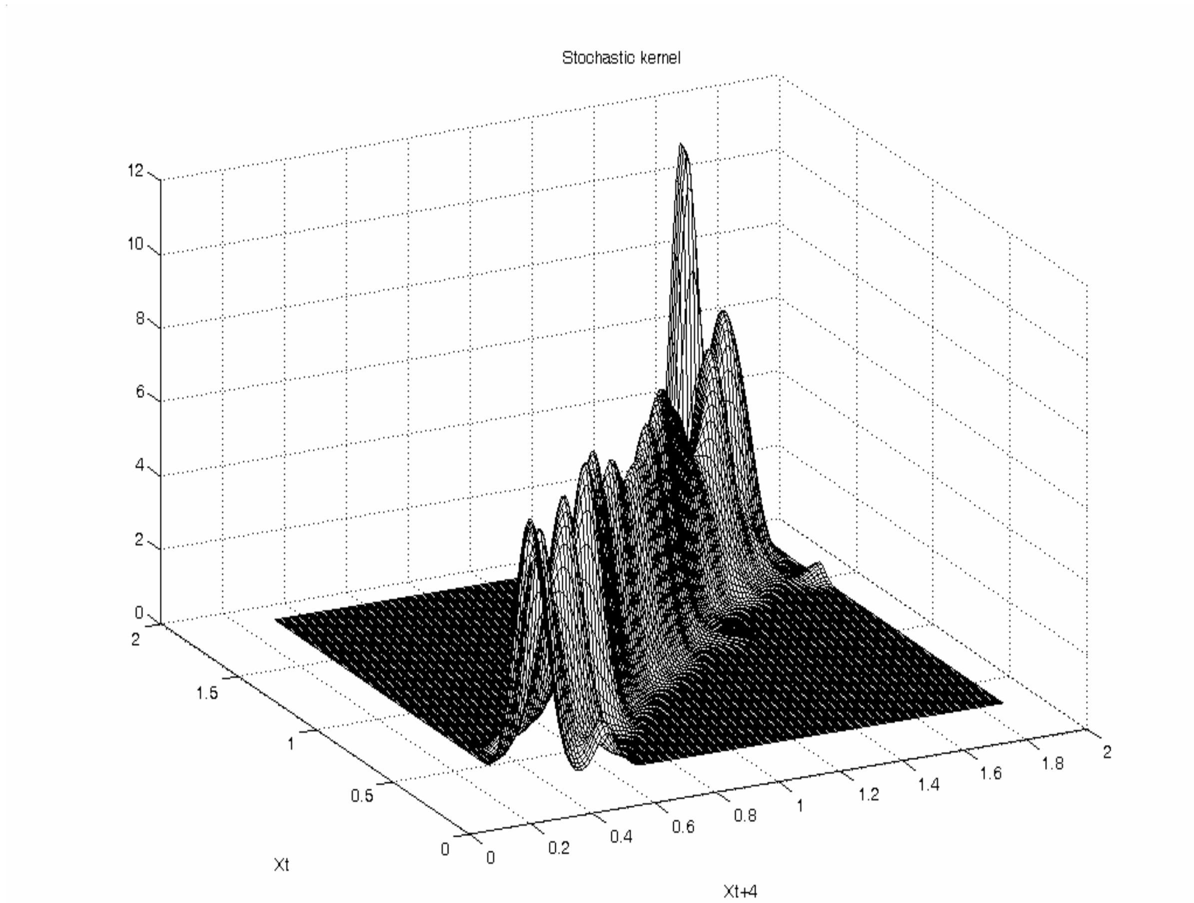


Figure 1. Estimated $f_{\tau=4}(y|x)$ for EU regions: 1980-2000

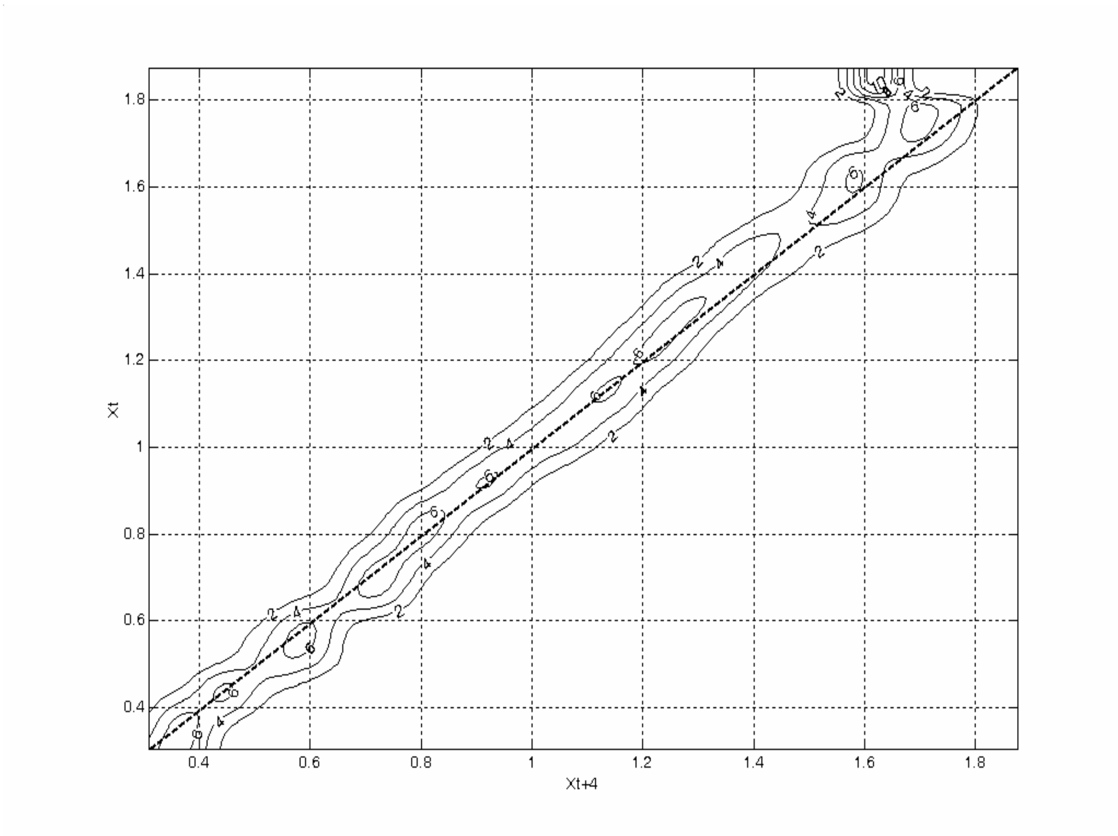


Figure 2 Contour plot of estimated $f_{\tau=4}(y|x)$

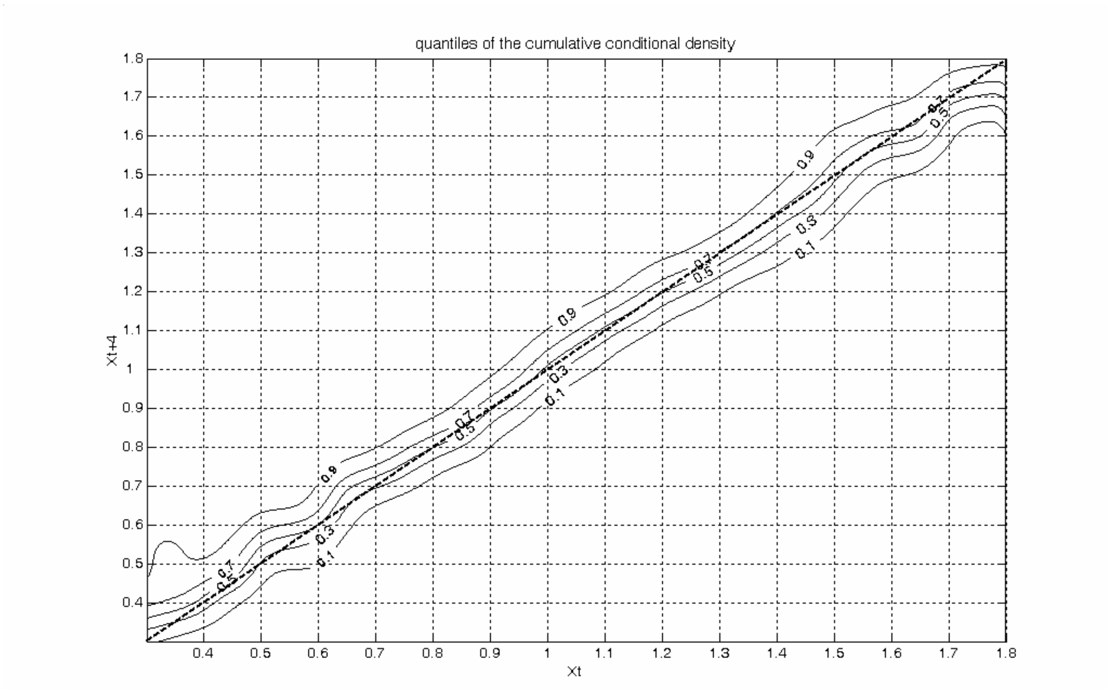


Figure 3 Nonparametric quantiles of $F_{\tau}(y|x)$

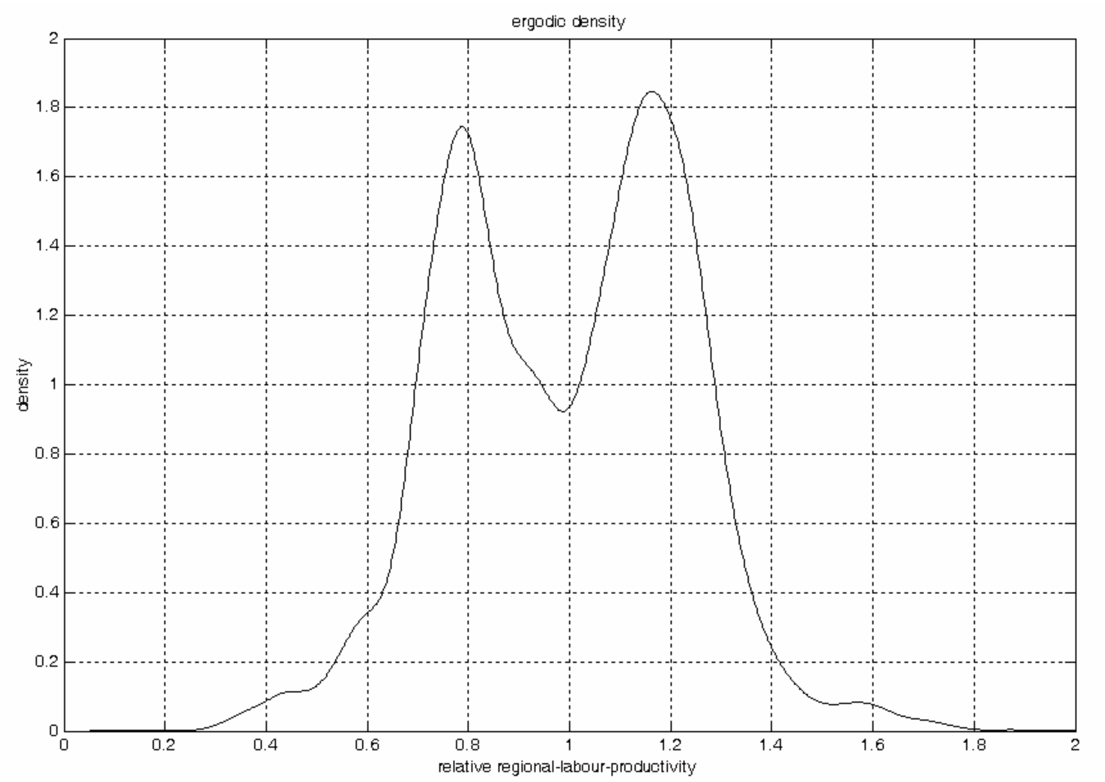


Figure 4. ergodic density $f_\infty(y)$

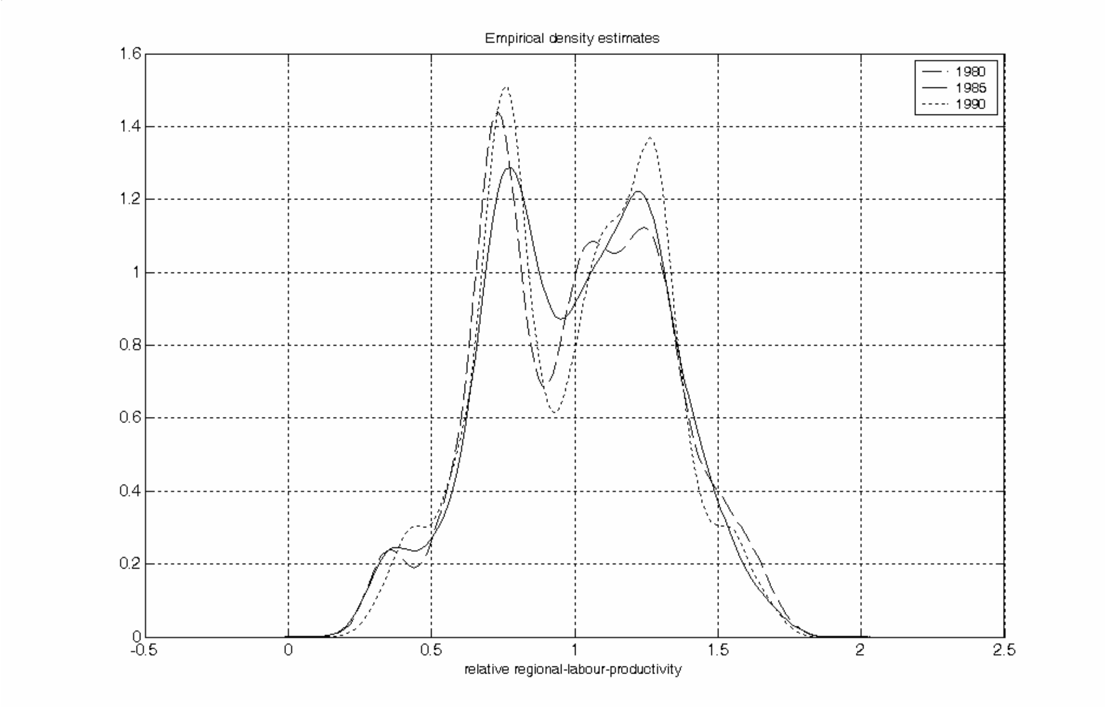


Figure 5. Empirical density estimates: relative regional productivity in 1980, 1985 and 1990.

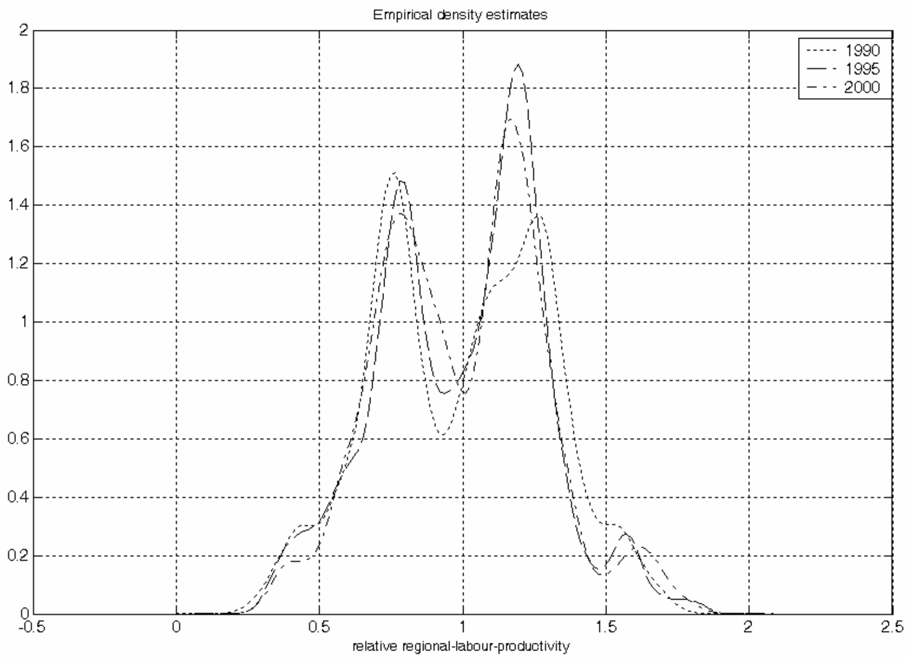


Figure 6. Empirical density estimates: relative regional productivity in 1990, 1995 and 2000.

Table. 1 Bootstrap based modality tests (1000reps)
(relative GVA/employment in 1995 €)

| | h critical | | | | P values | | | |
|---|---|---|---|---|---|---|---|---|
| | m=1 | m=2 | m=3 | m=4 | m=1 | m=2 | m=3 | m=4 |
| 1980 | 0.1650 | 0.0770 | 0.0740 | 0.0400 | 0.0050 | 0.2560 | 0.0500 | 0.8890 |
| 1985 | 0.1600 | 0.0770 | 0.0500 | 0.0420 | 0.0010 | 0.2290 | 0.6860 | 0.7260 |
| 1990 | 0.1710 | 0.0570 | 0.0550 | 0.0480 | 0.0020 | 0.6880 | 0.3220 | 0.2540 |
| 1995 | 0.1370 | 0.0790 | 0.0480 | 0.0420 | 0.0230 | 0.2080 | 0.7800 | 0.6680 |
| 2000 | 0.1450 | 0.0910 | 0.0550 | 0.0400 | 0.0070 | 0.0830 | 0.4210 | 0.6690 |

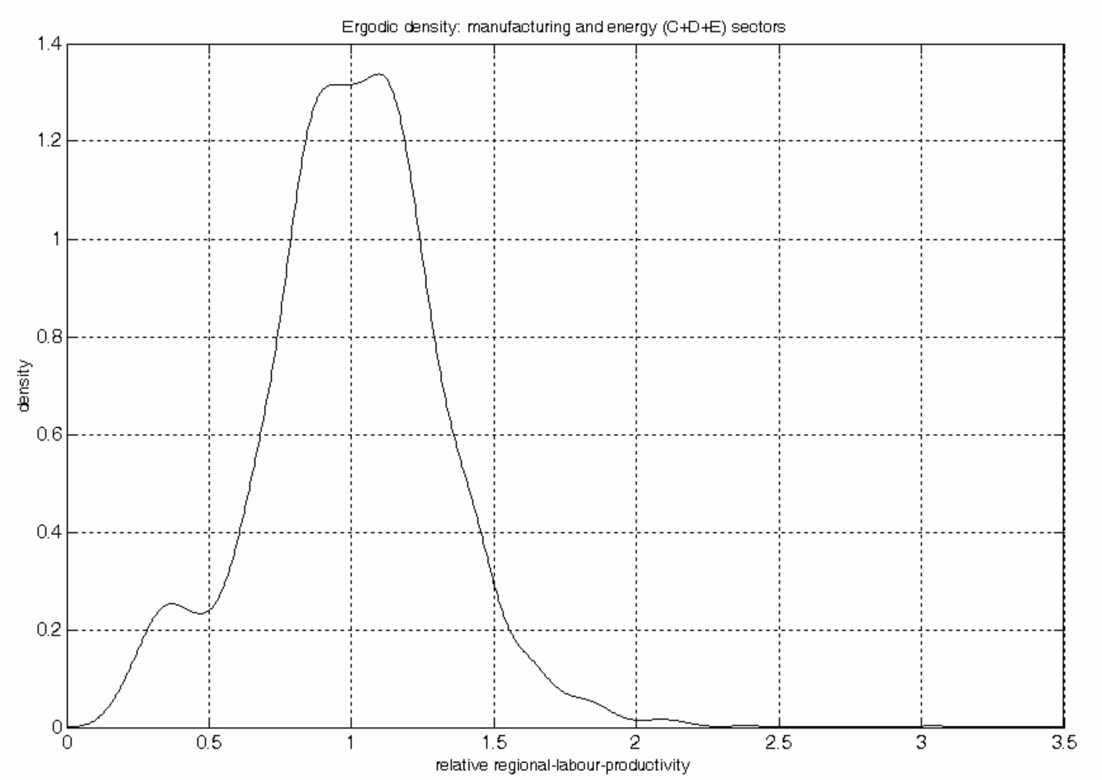


Figure 7. Ergodic density: manufacturing and energy sectors.

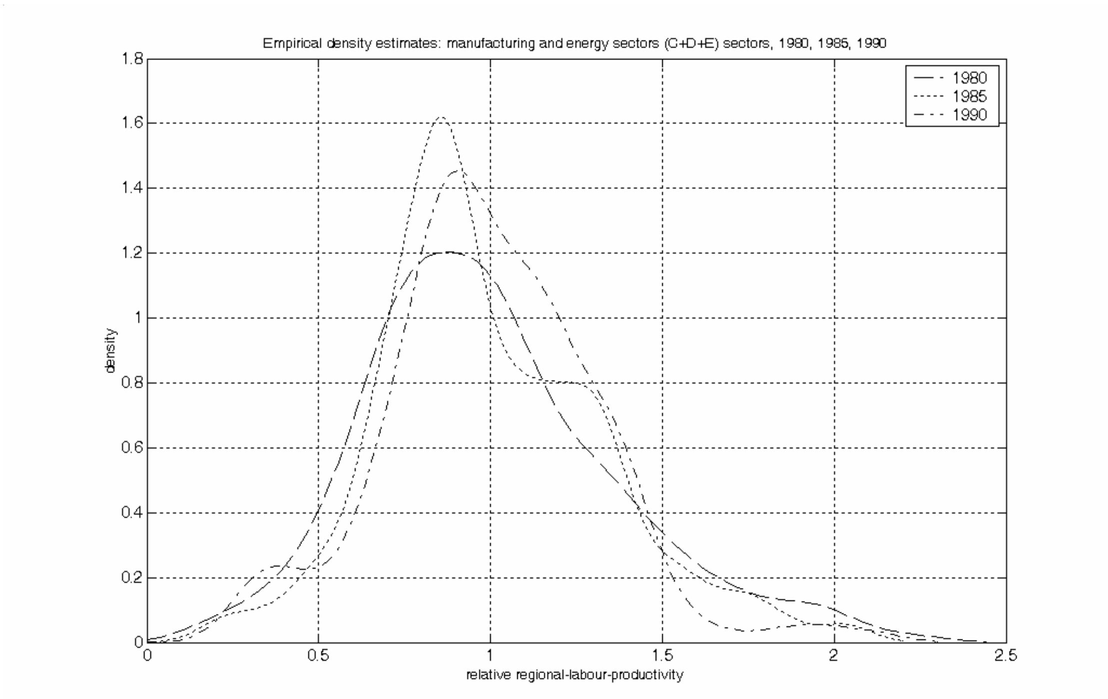


Figure 8. Empirical density estimates: manufacturing and energy sectors, 1980, 1985 and 1990.

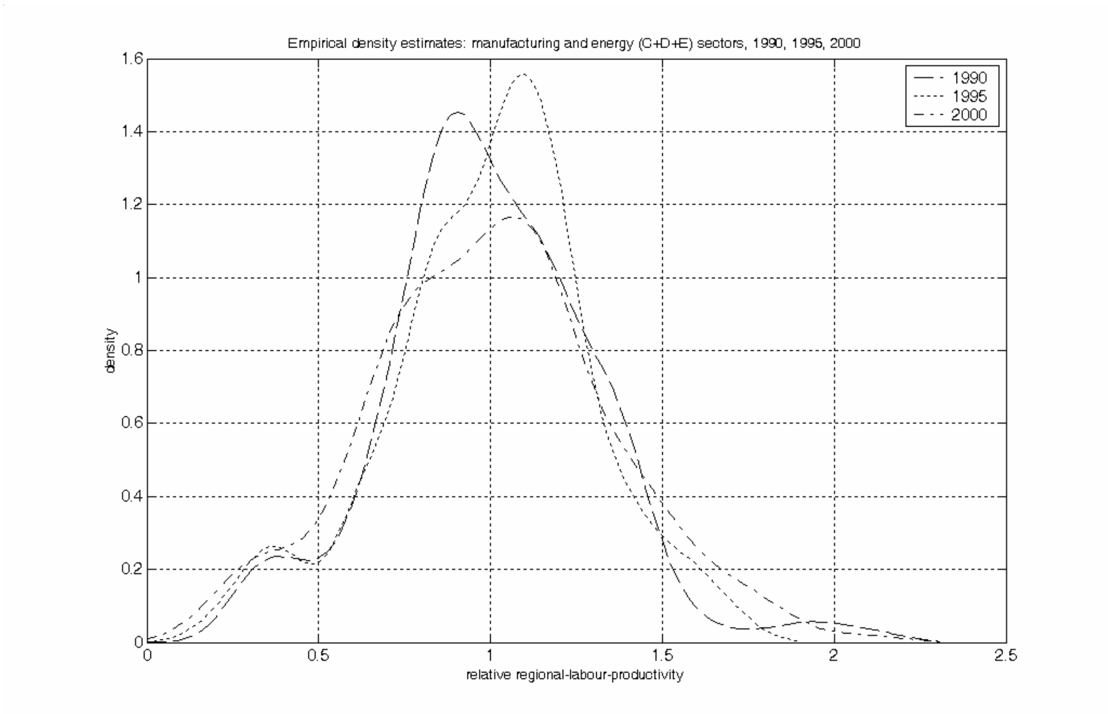


Figure 9. Empirical density estimates: manufacturing and energy sectors, 1990, 1995 and 2000.

Table. 2 Bootstrap based modality tests (1000reps): manufacturing and energy sectors

| | h critical | | | | P values | | | |
|---|---|---|---|---|---|---|---|---|
| | m=1 | m=2 | m=3 | M=4 | m=1 | m=2 | m=3 | m=4 |
| 1980 | 0.1000 | 0.0930 | 0.0780 | 0.0690 | 0.6320 | 0.2130 | 0.2480 | 0.2350 |
| 1985 | 0.0790 | 0.0700 | 0.0660 | 0.0580 | 0.8950 | 0.7960 | 0.5590 | 0.5220 |
| 1990 | 0.1410 | 0.0960 | 0.0610 | - | 0.1980 | 0.1890 | 0.7720 | - |
| 1995 | 0.1030 | 0.0720 | 0.0520 | 0.0510 | 0.1130 | 0.3190 | 0.6940 | 0.3360 |
| 2000 | 0.0980 | 0.0940 | 0.0890 | 0.0540 | 0.4890 | 0.1440 | 0.0410 | 0.7890 |

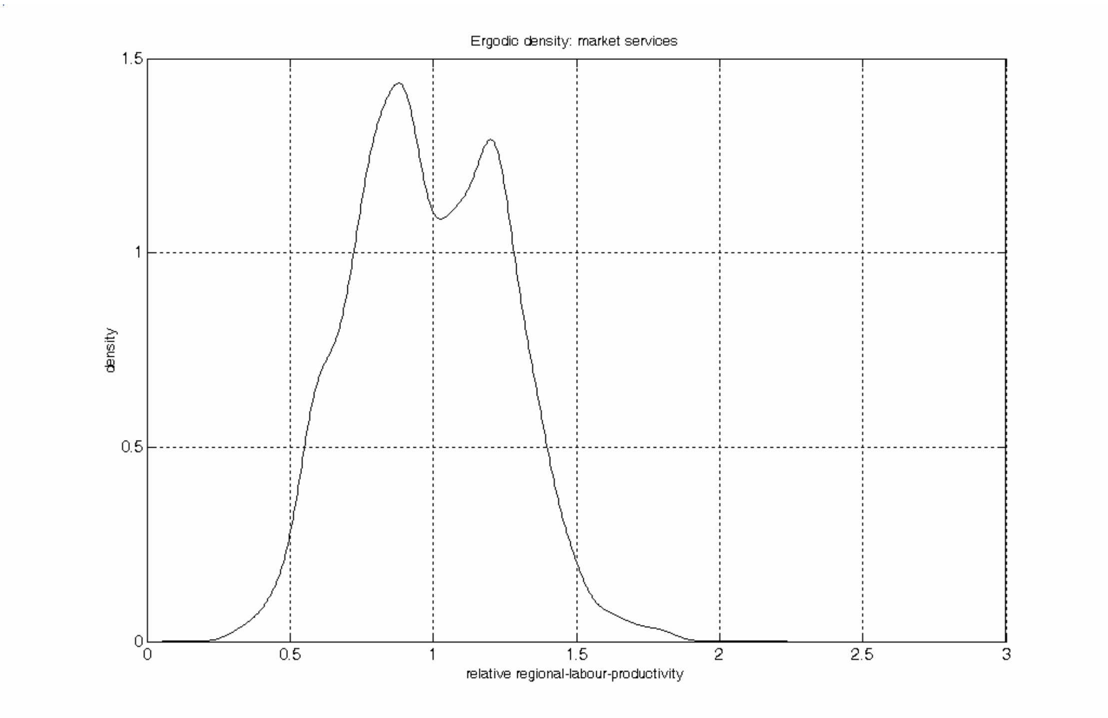


Figure 10. Ergodic density: market-services sectors.

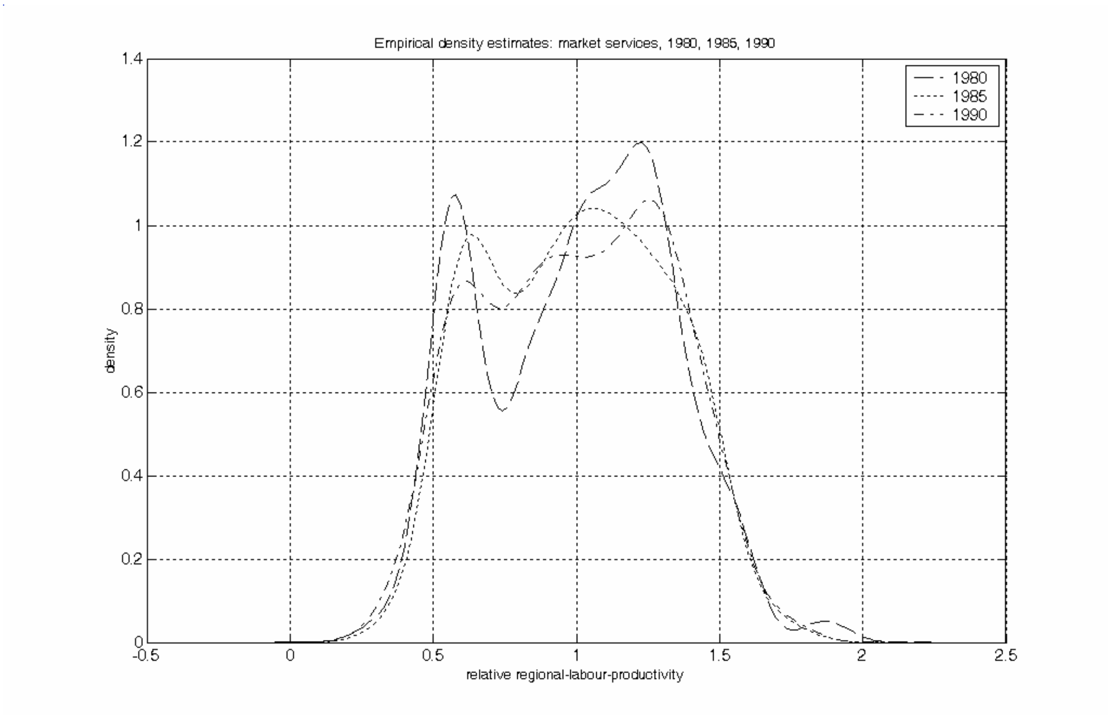


Figure 11. Empirical density estimates: market-services sectors, 1980, 1985 and 1990.

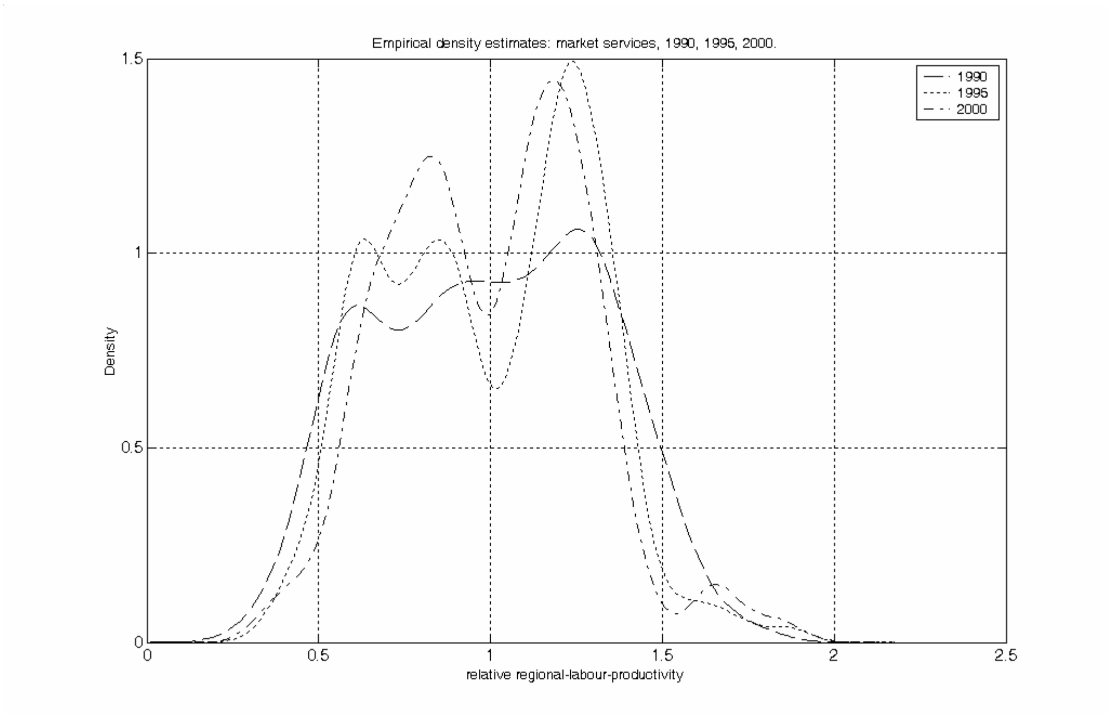


Figure 12. Empirical density estimates: market-services sectors, 1990, 1995 and 2000.

Table. 3 Bootstrap based modality tests (1000reps): market-services sectors

| | h critical | | | | P values | | | |
|---|---|---|---|---|---|---|---|---|
| | m=1 | m=2 | m=3 | m=4 | m=1 | m=2 | m=3 | m=4 |
| 1980 | 0.1530 | 0.0930 | 0.0610 | 0.0500 | 0.0550 | 0.2430 | 0.5720 | 0.5520 |
| 1985 | 0.1290 | 0.0520 | 0.0450 | - | 0.2120 | 0.9700 | 0.9220 | - |
| 1990 | 0.1160 | 0.1000 | 0.0610 | 0.0600 | 0.4530 | 0.0590 | 0.3750 | 0.0790 |
| 1995 | 0.1680 | 0.0890 | 0.0590 | 0.0550 | 0.0100 | 0.2560 | 0.5180 | 0.2080 |
| 2000 | 0.1440 | 0.0990 | 0.0540 | 0.0420 | 0.0160 | 0.1140 | 0.6690 | 0.7820 |

**Appendix:** list of NUTS included in the analysis

| | | | |
|---|---|---|---|
| Belgium | Bruxelles-Brussel | Spain | Galicia |
| | Antwerpen | | Asturias |
| | Limburg | | Cantabria |
| | Oost-Vlaanderen | | Pais Vasco |
| | Vlaams Brabant | | Navarra |
| | West-Vlaanderen | | Rioja |
| | Brabant Wallon | | Aragon |
| | Hainaut | | Madrid |
| | Liege | | Castilla-Leon |
| | Luxembourg(BE) | | Castilla-la Mancha |
| | Namur | | Extremadura |
| Germany | Stuttgart | | Cataluna |
| | Karlsruhe | | Com. Valenciana |
| | Freiburg | | Baleares |
| | Tubingen | | Andalucia |
| | Oberbayern | | Murcia |
| | Niederbayern | | Ceuta y Melilla |
| | Oberpfalz | | Canarias |
| | Oberfranken | France | Ile de France |
| | Mittelfranken | | Champagne-Ard. |
| | Unterfranken | | Picardie |
| | Schwaben | | Haute-Normandie |
| | Bremen | | Centre |
| | Hamburg | | Basse-Normandie |
| | Darmstadt | | Bourgogne |
| | Giessen | | Nord-Pas de Calais |
| | Kassel | | Lorraine |
| | Braunschweig | | Alsace |
| | Hannover | | Franche-Comte |
| | Luneburg | | Pays de la Loire |
| | Weser-Ems | | Bretagne |
| | Dusseldorf | | Poitou-Charentes |
| | Koln | | Aquitaine |
| | Munster | | Midi-Pyrenees |
| | Detmold | | Limousin |
| | Arnsberg | | Rhone-Alpes |
| | Koblenz | | Auvergne |
| | Trier | | Languedoc-Rouss. |
| | Rheinhessen-Pfalz | | Prov-Alpes-Cote d'Azur |
| | Saarland | | Corse |
| | Schleswig-Holstein | Ireland | Border |
| Greece | Anatoliki Makedonia | | Southern and Eastern |
| | Kentriki Makedonia | Italy | Piemonte |
| | Dytiki Makedonia | | Valle d'Aosta |
| | Thessalia | | Liguria |
| | Ipeiros | | Lombardia |
| | Ionia Nisia | | Trentino-Alto Adige |
| | Dytiki Ellada | | Veneto |
| | Sterea Ellada | | Fr.-Venezia Giulia |
| | Peloponnisos | | Emilia-Romagna |

| | | | |
|---|---|---|---|
| | Attiki | | Toscana |
| | Voreio Aigaio | | Umbria |
| | Notio Aigaio | | Marche |
| | Kriti | | Lazio |
| Netherlands | Friesland | | Abruzzo |
| | Drenthe | | Molise |
| | Overijssel | | Campania |
| | Gelderland | | Puglia |
| | Utrecht | | Basilicata |
| | Noord-Holland | | Calabria |
| | Zuid-Holland | | Sicilia |
| | Zeeland | | Sardegna |
| | Noord-Brabant | United Kingdom | Tees Valley and Durham |
| | Limburg | | Northumb. et al. |
| | Burgenland | | Cumbria |
| Portugal | Norte | | Cheshire |
| | Centro | | Greater Manchester |
| | Lisboa e V.do Tejo | | Lancashire |
| | Alentejo | | Merseyside |
| | Algarve | | East Riding |
| | Acores | | North Yorkshire |
| | Madeira | | South Yorkshire |
| Finland | Ita-Suomi | | West Yorkshire |
| | Etela-Suomi | | Derbyshire |
| | Lansi-Suomi | | Leics. |
| | Pohjois-Suomi | | Lincolnshire |
| | Aland | | Hereford et al. |
| Denmark | Denmark | | Shrops. |
| Luxembourg | Luxembourg | | West Midlands (county) |
| Austria | Niederosterreich | | East Anglia |
| | Wien | | Bedfordshire |
| | Karnten | | Essex |
| | Steiermark | | Inner London |
| | Oberosterreich | | Outer London |
| | Salzburg | | Berkshire et al. |
| | Tirol | | Surrey |
| | Vorarlberg | | Hants. |
| Sweeden | Stockholm | | Kent |
| | Ostra Mellansverige | | Gloucester et al. |
| | Sydsverige | | Dorset |
| | Norra Mellansverige | | Cornwall |
| | Mellersta Norrland | | Devon |
| | Ovre Norrland | | West Wales |
| | Smaland med oarna | | East Wales |
| | Vastsverige | | North East Scot. |
| | | | Eastern Scotland |
| | | | South West Scot. |
| | | | Highlands and Islands |
| | | | Northern Ireland |