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TFP CONVERGENCE ACROSS EUROPEAN REGIONS: A COMPARATIVE SPATIAL DYNAMICS ANALYSIS

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WORKING PAPERS

2010/30

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Titolo: TFP CONVERGENCE ACROSS EUROPEAN REGIONS: A COMPARATIVE SPATIAL DYNAMICS ANALYSIS

ISBN: 978 88 84 67 633 7

Prima Edizione: Dicembre 2010

Via Is Mirrionis, 1
09123 Cagliari
Tel./Fax 070 291201
www.cuec.it

TFP convergence across European regions: a comparative spatial dynamics analysis

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Abstract

This paper proposes a fixed-effect panel methodology that enables us to simultaneously take into account both TFP and traditional neoclassical convergence. We analyse a sample of 199 regions in EU15 (plus Norway and Switzerland) between 1985 and 2006 and find the absence of an overall process of TFP convergence as we observe that TFP dispersion is virtually constant across the two sub-periods. This result is proved robust to the use of different estimation procedures such as simple LSDV, spatially corrected LSDV, Kiviet-corrected LSDV, and GMM à la Arellano and Bond. However, we also show that this absence of a strong process of global TFP convergence hides interesting dynamic patterns across regions. These patterns are revealed by the use of recent exploratory spatial data techniques that enable us to obtain a complete picture of the complex EU cross-regions dynamics. We find that, between 1985 and 2006, there has been numerous regional miracles and disasters in terms of TFP performance and that polarization patterns have significantly changed along time. Overall, results seem to suggest that a few TFP leaders are emerging and are distancing themselves from the rest, while the cluster of low TFP regions is increasing.

Keywords: TFP, technology catching up, panel data, exploratory spatial data analysis.
JEL Classification: , C23, O47, O33, R11

Acknowledgments: The research leading to these results has received funding from the ESPON project KIT, Knowledge, Innovation, Territory.

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1. Introduction

Even if a large body of economic theory suggests that differences in estimated Total Factor Productivity (TFP) should imply the presence of flows of technology from advanced to less developed areas, data often reveal that these diffusion processes are neither effortless nor instantaneous, and persistent differences in the rate of technology adoption are observed together with weak (or the absence of) processes of absolute convergence in income per capita (Pritchett, 1997; Durlauf *et al.*, 2005; Grier K. and Grier R., 2007). This evidence is usually explained by differences in human capital stocks, as firstly suggested by Nelson and Phelps (1966), and/or by institutional quality heterogeneity, (Hall and Jones, 1999; Acemoglu *et al.*, 2001 and 2006, Comin *et al.*, 2009), and/or by the existence of monopoly rights of various forms that create a barrier to technology adoption, as in Parente and Prescott (1999). However, more puzzling is the evidence that slow processes of technology adoption are observed even across similar leading countries of the world economy (Comin and Hobijn, 2004 and Comin *et al.* 2006) or across regions within the same country or within union of states (see Magrini, 2004, for a review).

Following a methodology firstly suggested by Islam (1995) and further extended by Di Liberto *et al.* (2008), in this paper we focus on TFP di/convergence across European regions assessing the presence of TFP heterogeneity and dynamics by means of a fixed-effects panel estimator in a standard convergence equation framework.[1] One of the main features of this approach is that it makes possible to examine (likely) cases in which TFP differences in levels are not constant since it allows to estimate TFP at different points in time and test directly for the presence of TFP convergence. In particular, in this framework TFP levels are estimated by means of growth regressions in which the contribution of factor accumulation – namely, capital deepening – to income convergence is separately taken into account. As stressed by Bernard and Jones (1996), this is not an easy task in empirical analysis but it is extremely important since it limits the otherwise likely risk of overstating the role of TFP dynamics within convergence processes. The difficulty rests on the fact that the estimation of TFP levels and the identification of the role of technology diffusion within income convergence is not simple. What is usually needed for computing TFP is

[1] A similar approach can also be found in Dettori *et al.* (2010) and Marrocu *et al.* (2010).

a measure of output disparities which is not due to different input levels but occurs, instead, through marginal product increases.[2]

The robustness of our results in terms of TFP estimates is assessed by comparing different estimators, namely, an Ordinary Least Squares (OLS), a Least Square with Dummy Variable (LSDV), a spatial-corrected LSDV (Anselin *et al.*, 2008), a biased-corrected LSDV estimator (Kiviet, 1995) and a Generalized Method of Moments estimator (GMM, Arellano-Bond, 1991). We use a procedure suggested by Bond *et al.* (2001) and Monte Carlo results to select plausible estimates. Results are then analysed by focusing on the underlying spatial dimension of TFP across regions both from a static and a dynamic perspective following some recent contributions by Rey *et al.* (2010) and Rey and Ye (2010).

We use data on per capita Value Added (VA) of 199 regions in 17 countries (EU15 plus Norway and Switzerland) over the period 1985-2006. It is worth underlining that this time span is longer than those used by most of the other studies on TFP dynamics across EU regions and includes the decade characterized by the Information and Technology (IT) revolution, a phenomenon known to be the source of a significant asymmetric shock on productivity levels, with the more developed economies as the major beneficiaries. We choose EU15+2 for a twofold reasons, a practical one and another more substantial one. The former has to do with time series availability, which is restricted to a shorter period for regions pertaining to new accession countries. The latter relates to the fact that we prefer to preliminary test the catching up hypothesis for those regions where institutional and economic settings are similar and therefore with an ideal scenario for technology transfer.

Our results confirm that cross-region gaps in TFP levels are significant, that they are persistent, and that they are an important component of VA per capita dynamics. In particular, we do not observe a process of global convergence in TFP, as it is not detected in VA per capita. At the same time this does not imply the absence of cross-region dynamics in TFP. Conversely, during the two decades under examination, we notice the presence of strong intra-distribution movements with significant changes in regional rankings and cluster composition. To analyse such movements we focus on geographic

[2] A large array of methodologies is currently available to estimate TFP and none has emerged as a recognized standard. See Del Gatto *et al.* (2010) for a recent survey.

aspects to assess if they depend on the spatial environment which characterises each region. We, thus, find the presence of both global and local spatial dependence in TFP levels, that is, cluster effects across borders. Finally, thanks to new visualisation techniques we highlight that polarisation patterns have changed profoundly along time.

The paper is organized as follows. In section 2 we describe our methodology to estimate TFP levels at different point in time. Section 3 discusses the selection of the estimator which suits our case better and presents our evidence on degrees of cross-region TFP heterogeneity and on TFP convergence. Section 4 examines the role of space in the evolution of regional TFP distributions by means of some traditional and some most up-to-date tools of exploratory spatial data analysis (ESDA). Conclusions are in section 5.

2. A Panel Data approach to estimate TFP convergence

Islam (1995) was among the first to suggest to investigate cross-country (or region) TFP heterogeneity by using an appropriate fixed-effect panel estimator.[3] In particular, the author extended the standard Mankiw *et al.* (1992) structural approach by allowing TFP levels to vary across individual economies, together with saving rates and population growth rates. This approach uses suitable panel techniques to estimate a standard convergence equation:

$$y_{it} = \beta y_{it-\tau} + \sum_{j=1}^{2} \gamma_j x_{j,it} + \eta_t + \mu_i + v_{it} \qquad j=1,2 \qquad (1)$$

where the dependent variable is the logarithm of *per capita* VA (measured in terms of population working age), v_{it} is the transitory term that varies across countries. The remaining terms are:

[3] See also Caselli *et al.* (1996) and Islam (2003) among others.

$$x_{1,it} = \ln (s_{it}) \tag{2}$$

$$x_{2,it} = \ln (n_{it} + g + \delta) \tag{3}$$

$$\gamma_1 = (1 - \beta)\frac{\alpha}{1-\alpha} \tag{4}$$

$$\gamma_2 = -(1 - \beta)\frac{\alpha}{1-\alpha} \tag{5}$$

$$\mu_i = -(1 - \beta)\ln A(0)_i \tag{6}$$

$$\eta_t = g(t_2 - \beta t_1) \tag{7}$$

where $A(0)_i$ represents the initial level of technology, and s, n, δ are, respectively, the saving rate, the population growth rate, the depreciation rate; *g* is the exogenous rate of technological change,[4] assumed to be invariant across individual economies; α is the usual capital share of a standard Cobb-Douglas production function; finally, $\beta = e^{-\lambda\tau}$, where $\lambda = (1 - \alpha)(n + g + \delta)$ represents the convergence parameter and $\tau = t_2 - t_1$ is the time span considered.

In this specification, technology is represented by two terms. The first term, μ_i, is a time-invariant component that varies across economies and should control for various unobservable factors. The second, η_t, is the time trend component (eq. 7) that captures the growth rate of the technology frontier assumed constant across individuals. Once we have the estimated individual intercepts, we can obtain an index of TFP by computing:

$$A(0)_i = \exp\left(\frac{\mu_i}{1-\beta}\right) \tag{8}$$

Since TFP estimates include all unobservable components assumed to be different across countries but constant over time such as technology gaps (more on this presently), culture and institutions, and since these components are likely to be correlated with other regressors, a fixed effect estimator is appropriate. If we apply a least square with dummy variables (LSDV henceforth) to equation (1), individual effects may be directly estimated. With other available estimators, such as Within Group or Arellano-Bond (1991), estimates of μ_i and, thus, of

[4] As is standard in this literature, $(g + \delta)$ is assumed equal to 0.05.

$A(0)_i$ can be obtained through equation (1) by:

$$(\hat{\mu}_i + \hat{u}_{it}) = y_{it} - \hat{\beta} y_{it-\tau} - \sum_{j=1}^{2} \hat{\gamma}_j x_{j,it} \tag{9}$$

$$\widehat{\overline{\mu_i}} = \frac{1}{T} \sum (\hat{\mu}_i + \hat{u}_{it}) \tag{10}$$

Following Di Liberto *et al.* (2010) we use equation (1) to test for the presence/absence of technological convergence. That is, we estimate μ_i and, thus, individual TFP values over several subsequent periods, in order to test whether the observed time pattern is consistent either with the catch-up hypothesis or with the alternative hypothesis that the current degree of technology heterogeneity across regions is constant or even increasing over time.[5]

Our period of analysis, from 1985 to 2006 includes some years which have been strongly influenced by the introduction of IT technologies. In terms of TFP convergence, such years are important since the development of IT have seen "… a rapidly rising source of aggregate productivity growth throughout the 1990's".[6] More precisely, we use different datasets (Cambridge Econometrics and Eurostat) to estimate the following equation:

$$\tilde{y}_{it} = \beta \tilde{y}_{it-\tau} + \sum_{j=1}^{2} \gamma_j \tilde{x}_{j,it} + \mu_i + u_{it} \tag{11}$$

$$\tilde{y}_{it} = y_{it} + \bar{y}_t \quad , \tilde{x}_{it} = x_{it} + \bar{x}_t \tag{12}$$

where $\bar{y}_t$ and $\bar{x}_t$ are the EU regional averages in period t: that is, data are taken in difference from the sample mean, in order to control for the presence of a time trend component η_t and of a likely common stochastic trend (the common component of technology) across

[5] Splitting a longer period in several sub-periods has an additional advantage, since the longer the time dimension of the panel, the higher the risk that differences in TFP levels are not constant due to the presence of technological diffusion. In other words, equation (1) is likely to be an approximation of the real process – an approximation that deteriorates as the length of the period under analysis increases.

[6] See Jorgenson (2005).

countries.[7] We use a three-year time span in order to control for business cycle fluctuations and serial correlation, which are likely to affect the data in the short run. Moreover, the use of a three-year time span enables us to apply all available observations and obtain a sample with T=8, which is the longest possible one.[8] Finally, all regressors are taken at their *t-3* level to control for likely endogeneity problems.

3. Cross-region TFP levels in a dynamic panel

The first problem to solve when estimating a dynamic panel data model such as the one represented by equation (11) is the selection of the best estimator. The solution is not simple since even consistent estimators are characterized by small sample problems. To this end we carefully compare the results obtained by using four different fixed effects estimators: LSDV, LSDV with spatial correction suggested by Anselin *et al.* (2008) and the one with the correction advocated by Kiviet (1995) and the GMM suggested by Arellano and Bond (1991). In our choice of estimators we do not include the system-GMM suggested by Blundell and Bond (1998) and Minimum Distance, both used by Islam (2003). Reason for this choice is twofold. First of all, the theoretical restrictions on which the system-GMM estimator is based do not hold in this context.[9] Secondly, the use of the Minimum Distance estimator has been highly criticised within the growth literature and there is a lack of empirical analysis that compares the performance of this estimator with other available estimators[10]. In other words, the use of the Minimum Distance and system GMM to estimate fixed effects, and thus TFP levels, do not represent an optimal choice in this context.

As we specify above, our panel includes the period 1985-2006 for 199 regions. Using the three-year time span (or $\tau=3$) implies that we

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[7] The Levin *et al.* (2002) panel unit-root test performed on the demeaned GDP series reject the hypotheses that series are non stationary.

[8] Therefore, our sample includes the following years: 1985, 1988, 1991, 1994, 1997, 2000, 2003 and 2006.

[9] In particular, this methodology requires that first-difference Δy_{it} are not correlated with μ_i (see Bond *et al.* 2001), and this implies that in order to implement this estimator we need to assume the absence of technological catching-up. If efficiency growth is related to initial efficiency, the first difference of log output might be correlated with the individual effect. On this see also Hauk and Wacziarg (2009).

[10] For more on the use of the MD estimator in growth analysis see Caselli *et al.* (1996) and Islam (2003).

are left with T=8 observations for each region. Estimates over the whole sample period are reported in Table 1. For each regression we include both our estimates and the implied value of the structural parameter $\hat{\lambda}$, i.e. the speed of the convergence parameter.

In analysing our results, we follow the procedure proposed by Bond *et al.* (2001) and consistent with the literature on partial identification[11]. Their suggestion is to use the results obtained with LSDV and a pooling OLS estimator as benchmarks to detect a possible bias in our other estimates. In particular, results show that in dynamic panels the OLS coefficient in the lagged dependent variable is known to be biased upwards. Conversely, LSDV, while consistent for large T, is characterised by small sample problems and it is known to produce downward biased estimates on the AR(1) coefficient in small samples. Therefore, in our specific case, since we presume that the true parameter value lies somewhere between $\hat{\beta}_{OLS}$ and $\hat{\beta}_{LSDV}$, we expect it to be between 0.98 and 0.60 (as shown in Table 1) and we will exclude from our analysis estimators that produce results out of this range.

When equation (11) is estimated with LSDV (column 2) we find that regional dummy coefficients are almost $\hat{\mu}_i$ invariably statistically significant. In particular, the F-test of the joint hypothesis that all the coefficients on our dummies are equal to zero is 23.15 (p-value=0.00) and clearly rejects the hypothesis of no difference among regions.[12] Moreover, we find an AR(1) coefficient of 0.60 and a corresponding high speed of convergence of 17%. Among the regressors, both the coefficients on the lagged dependent variable and on population growth are significant and have the expected sign, while the coefficient on human capital is not significant.[13] These results will be confirmed when other estimation procedures are used.

[11] As Manski (2007) puts it, "a parameter is partially identified if the sampling process and maintained assumptions reveal that the parameter lies in a set, its 'identification region', that is smaller than the logical range of the parameter but larger than a single point".

[12] Note that individual effects are not directly estimated when GMM-AB1 and KIVIET are used.

[13] The lack of empirical support for human capital in convergence regressions based on large international datasets is a well known problem. A number of possible explanations have been put forward. See Pritchett (1997), Temple (1999), and Krueger and Lindahl (2001).

According to several authors[14], the study of convergence across states and regions should take into account the possibility for spatial spillovers across territorial units which may lead to spatial dependence[15]. Such a possibility has been tested[16] and the suggested model, the so called spatial error model (or SEM, see Anselin, 1988), has been estimated by means of Maximum Likelihood and results are reported in column 3. They are very much alike those obtained with LSDV. We will further investigate the spatial dependence problem issue since it will be the core of our descriptive analysis in the following section.

Our next estimator is based on Kiviet (1995), which addresses the problem of the LSDV finite sample bias by proposing a small sample correction[17]. As expected, the use of the KIVIET correction procedure increases the LSDV parameter. In column 4, the coefficient of the lagged dependent variable is 0.74, with a decrease in the corresponding speed of convergence measure to approximately 9%. Clearly KIVIET estimate satisfies the aforementioned Bond *et al.* (2001) criterion since the estimated AR(1) coefficient lies between $\hat{\beta}_{OLS}$ and $\hat{\beta}_{LSDV}$.[18] Further, in favour of the use of KIVIET we also find Montecarlo results. These studies find that for balanced panel and small (less or equal to ten) or

[14] Interesting contributions are Rey and Montouri (1999), Lopez-Baso et al. (2004), Ertur C. and Koch W. (2007) and Basile (2009). The latter author, in particular, proposes an analysis of the intra-distribution dynamics of regional labour productivity (instead of TFP as in this paper) in Western Europe (EU15). He finds the existence of multiple equilibria in regional growth behavior in Europe with a clear spatial pattern.

[15] The presence of spatial dependence violates the assumption of independent error terms in different regions.

[16] The diagnostic tests applied to the LSDV model are two Lagrange Multiplier tests robust to local misspecification. The alternative model to correct for spatial autocorrelation which is outperformed by the spatial error model is the spatial lag model (see Anselin, 1988).

[17] The correct procedure would be to move from model 3 to model 4 without losing the correction for spatial dependence. However the spatial error model cannot be estimated together with the Kiviet correction. Nonetheless the comparison of the ranking shows that results are very similar.

[18] The analysis is performed assuming a bias correction up to order O(1/T) and Anderson Hsiao as consistent estimator in the first step. Results are not sensitive to the use of alternative options: the Spearman rank order coefficient obtained comparing TFP obtained with KIVIET (Anderson-Hsiao) and KIVIET (Arellano-Bond) is extremely high, 0.997. Standard errors are calculated through bootstrapping.

moderate T (T=30), such as the one we usually find in convergence literature, this estimator has more attractive properties than other available estimators.

We finally extend our comparison to the GMM-AB estimator[19]. This may be performed under very different assumptions about the endogeneity of the included regressors. In this study we adopt three different hypotheses on the additional regressors $x's$. First, Model 4 (GMM-AB1) in Table 1 assumes that all $x's$ are strictly exogenous; secondly, Model 5 (GMM-AB2) assumes instead that all regressors are endogenous; finally, Model 6 (GMM-AB3) assumes predetermined regressors. While the estimated AR(1) coefficients do not suggest any presence of bias, conversely, the Sargan test in each of the three models implies that these specifications are not valid. Further, the estimated coefficients of the lagged dependent variable never satisfy the Bond *et al.* (2001) criterion: only GMM-AB1 has an estimated AR(1) coefficient almost identical to the lowest interval value, that is, $\hat{\beta}_{LSDV}$. As a consequence, in the remaining part of the paper we do not further use or report results based on this estimator.

[Table 1 around here]

With LSDV, SEM and KIVIET estimates in hand, we can, therefore, compute the TFP measures. Using KIVIET we obtain estimates of $\hat{A}(0)_i$ by means of eq. (8). In all cases, the TFP estimates $\hat{A}(0)_i$ are then used to compute $T\hat{F}P_i = \hat{A}(0)_i/\hat{A}(0)_{DK}$, with $\hat{A}(0)_{DK}$ being the estimated TFP value for Denmark. As we shall see, in our analysis this country/region is consistently recognised as the TFP leader. A closer inspection of our estimates would further reveal that best and worst performers are almost identical across the estimators. Moreover, table 2 reports the Spearman rank order correlation coefficients to compare TFP results obtained by our three estimators on which we focus our research. That is, the Spearman coefficient enables us to assess if the regional rankings in terms of TFP levels differ across the estimation

[19] Note that Blundell and Bond (1998) and Bond *et al.* (2001) show that, when T is small, and either the autoregressive parameter is close to one (highly persistent series), or the variance of the individual effect is high relative to the variance of the transient shock, then even the GMM-AB estimator is downward biased.

following procedures: LSDV, SEM and KIVIET. It is clear that regional rankings obtained with these three methods are remarkably similar, with the index always above 0.99. High values (from 0.92 to 0.95) are also obtained when we compare our estimates with the ranking of regional per capita value added in the initial year (VAP85).

[Table 2 around here]

To sum up, the pattern and the magnitude of TFP heterogeneity, independently on the chosen estimator, strongly confirm that cross-region TFP inequality is wide and that it is strongly associated with differences in per capita VA. In other words, a potential for technological catch-up of lagging regions does exist. In the following, we implement the same methodology to compute TFP at two points in time in order to assess to what extent that potential has occurred as an actual source of convergence. Since estimating TFP-levels for two sub-periods further exacerbates the problems associated with small sample bias we opt to carry on our analysis with the KIVIET estimator.[20] Spatial analysis is subsequently applied to these TFP estimates.

4. TFP convergence and spatial-dynamic analysis

To detect how much TFP convergence is present in our sample, we estimate TFP using the same methodology described in the previous section over two sub-periods: 1985-1997 and 1997-2006. As before, we estimate equation (11) and save the two different series of $\hat{\mu}_i$ and then compute the two indexes $T\hat{F}P_{i,1} = \hat{A}_{i,1}/\hat{A}_{DK,1}$ (for the initial period, 1985-97) and $T\hat{F}P_{i,2} = \hat{A}_{i,2}/\hat{A}_{DK,2}$ (for the subsequent period, 1997-2006). Estimation results are summarised in Table 3, where we focus on the KIVIET estimates even though the OLS and LSDV results are also shown for comparative reasons. Further, the whole set of estimated regional TFP values and the variation of the rankings in the two sub-periods are reported in Table A1 in the Appendix.

[20] See Kiviet (1995); Judson and Owen (1999); Everaert and Pozzi (2007). An exception can be found in Hauk and Wacziarg (2009) that suggest the use of a between estimator when measurement error is present. However, surprisingly, in their Monte Carlo analysis they do not consider the Kiviet estimator that is the preferred one in all other studies.

[Table 3 around here]

With these TFP estimates in hand, we can thus investigate the main features of the two distributions for the two periods and focus on their geographical characteristics in both a static and dynamic perspective. Contrary to most analyses of the distribution morphology of TFP along time, we do not treat each region as an a-spatial observational unit. We, therefore, accept the possibility that TFP dynamics can be related to geographical localisation and to phenomena which are dependent on spatial features, such as distance among agents. Following Ertur and Koch (2006) and Rey *et al* (2010), we investigate directly these geographical features which may prove crucial in the catching up process and the diffusion of technology. In particular, we focus on geographical distance which can influence some channels of communications, such as trade, externalities and knowledge circulation, between the origin and the destination regions. We, thus, implement a spatial criteria to study the distribution of regional disparities in total factor productivity in order to see if the local environment of each region relative to its neighbours has a role in determining TFP distribution and its dynamics along time.

The analysis below is mainly descriptive and it is based on global and local spatial measures of autocorrelation and on some new visualisation techniques of the latest developments of exploratory spatial data analysis (ESDA).

[Map 1a, b around here]

The starting point of ESDA is the inspection of the map of the phenomenon under examination. Maps 1a and 1b show TFP levels in our two sub-periods of analysis: 1985-97 and 1997-2006. As expected, regional TFP levels in the first period are higher in the centre of Europe, United Kingdom and in some Northern Scandinavian countries (especially Norway and Sweden). Backward regions are concentrated in the South of Europe. This confirms a well known stylized fact, with the northern EU regions at the top of the technology ladder and southern ones at the bottom. Among the former at the top of the ranking we find Denmark followed by some capital areas, that is Inner London, Zurich, Oslo and Brussels. At the bottom of the ranking the TFP laggard regions are all in southern Europe, that is in Italy, Spain, Portugal and Greece. The second period shows significant differences in terms of the spatial distribution of regional TFPs: some progress is recorded in United

Kingdom, Finland and Ireland. At the same time, some regions in central Europe (notably some French and German regions together with Italian regions in the centre-north) seem to have lost ground. Some capital regions keep their position (Ile de France and Madrid), some others not (Lazio). Therefore, comparing the two maps we observe evidence of a possible presence of polarisation of high and low levels of TFP. This might be a result of the IT revolution, which has been put in action by Northern regions and neglected in Central-South of Europe.

To further investigate the dynamics of polarisation, we use two popular and intuitive measures of inequality in regional economics, that is, the Theil index and the coefficient of variation which are therefore proposed in table 4. In case of convergence we expect their values to decrease from the first to the second period of analysis.

[Table 4 around here]

Conversely, we find that the main characteristic of our TFP distributions is the absence of an overall process of TFP convergence. Actually, both the Theil index and the CV increase along time implying a slight process of divergence in TFP levels across EU15 regions in the two decades starting from 1985. This is also suggested by Figure 1 which proposes the kernel distribution of TFP in the two periods. This figure, firstly, illustrates the absence of significant changes in the distribution between the initial TFP levels (dashed line) and subsequent TFP levels (straight line). Secondly, it suggests that a club of highly productive regions (those ones on the right hand side of the distribution) is getting away from the mass of the other less efficient regions.

[Figure 1 around here]

The absence of overall dynamics may, in fact, hide complex and interesting intra-distribution dynamic patterns. In particular, when we focus on detailed regional data we find that the intra-distribution dynamics across EU regions has been remarkable. Data show (see appendix for detail[21]) that EU regions have experienced significant

[21] For each region in Table A1 in the appendix we include both the first and second sub-period ranking position in terms of relative TFP levels and in the last two columns we include the change of rank in relative TFP levels and that observed in per capita VA levels between the initial and the final observation.

changes of rank. Among the losers we mainly find German, Italian and Netherland regions: Rheinhessen-Pfalz and Trentino (-100 positions), Hannover (-98), Arnsberg (-93), Groningen (-63). Conversely, with the exception of Ireland, among the winners results are less region specific but we identify many regions in UK and Ireland: Border (160), Southern and Eastern (+140), Herefordshire (+89), Northern Ireland (+85) are the best performers. Finally, notice that, even if not identical, the association between TFP and VA per capita is noteworthy: regions that have significantly improved in their TFP ranking are also the regions which have achieved high growth in VA per capita. That is, while obtaining fast growth in TFP is not simple, it appears to be a key factor in achieving fast VA per capita growth.

Moreover, since intra-distribution dynamic patterns may have or not a geographical basis, a further spontaneous question is: where are these mobile regions located? Are they close to each other? To answer this question we carry on with the application of ESDA.

One of the basic step of ESDA is the study of the spatial autocorrelation, a useful way to analyse territorial patterns in a certain period and along time. Local spatial movements can be traced by means of the Moran Scatterplot (Anselin, 1996), which illustrates different types of spatial association (each corresponding to a quadrant) between a region and its neighbours[22]. The Moran scatterplot in the two periods, reported in figures 2a and 2b respectively, is a useful tool since it immediately visualises spatial clustering of similar (HH and LL) values as much as cases of atypical values such as those in quadrant LH and HL. More specifically, the North-Eastern quadrant of the plot contains regions which have above average TFP surrounded by regions which also have high TFP (HH, high cluster regions); in the North-western quadrant we find below average TFP regions whose neighbours are above the TFP average (LH, backward regions); the South-western quadrant consist of regions with low TFP surrounded by other low TFP regions (LL, low cluster regions); while in the South-eastern quadrant one finds regions with high levels of TFP but with low TFP regions as their neighbours (HL, leader regions). The Moran scatterplot is also

[22] To model spatial dependence a connectivity grid, that is a spatial weight matrix, has to be specified. A spatial weight matrix W specifies exogenously the connection among regions and it can refer to either contiguity or to distance. In this paper we refer to contiguity, which implies that the w_{ij} element of the W matrix is set to unity when regions are contiguous and zero otherwise.

useful since it allow to assess the global spatial dependence (by means of the Moran I), which is represented by the slope of the linear regression (the dashed line) of the spatially lagged TFP on the original TFP.

Figures 2a and 2b provide useful information on both cross-sectional and time varying patterns of regional TFP clustering processes. Firstly, they show that in both periods spatial autocorrelation is present and significant. Nonetheless, as far as the global spatial autocorrelation is concerned, the Moran's I decreases from 0.366 to 0.251, which implies that clusters of similar regions (either with high or with low values) are becoming weaker along time The presence of regions which are characterised by the presence of positive spatial association is however constant along time with a quota of around 70% both in the first and in the second period[23]. We also identify a few outliers, that is regions which are far away from the bulk of regions either around the origin or along the dashed line. Outliers with respect the x axis (regions which are relatively poor but in rich surroundings) are Schleswig-Holsen in Germany (DEF) in the first period and Border in Ireland (IE01) in the second period; with respect to the y axis we find one region , that is Denmark (DK) in the first period and five regions in the second period, that is Southern and Eastern (IE02) in Ireland, Oslo (NO01), Inner London (UKI1) and Luxembourg (LU). These subset of regions are relatively richer than neighbouring regions, they are often capital regions and/or highly urbanised areas.

Another interesting aspect which can be extracted from the comparison of the two figures is the presence of an upward movement of the low-cluster regions (in the LL quadrant) that seem to gets less distant from the origin in the second period. A weak sign of TFP convergence for the backward regions.

[Figure 2 a,b around here]

However, a less reassuring picture for backward regions emerges from Table 5 that includes the share of regions in each cluster in both the first and the second period of the analysis. In particular, we find that the strength of the positive association for HH regions somewhat faints along time since the quota of such regions goes from 37% to 26% while,

[23] It is interesting to note that a quite similar result is obtained by Ertur and Koch (2006) in their analysis of income per capita across EU15 and EU27 regions: in 2000 they find 75% of positive spatial dependence.

conversely, the fraction of the low-cluster regions (LL regions) increases significantly, from 33% to 45%. That is, a non virtuous geographical clustering of TFP levels seems to appear in our regional TFP data[24]. Regional shares of dissimilar regions (LH and HL), that is, regions with TFP levels higher or lower with respect to their neighbouring regions, are much more stable, the former stays around 20% and the latter around 9%.

[table 5 around here]

Another helpful statistical tool is the so called Moran map, where the information provided in the Moran scatterplot, which discriminates regions with respect to the type of association, that is LL, HH, LH or H,L is positioned in a map[25]. Maps 2a and 2b, thus, distinguish regions corresponding to the four quadrants of the scatterplot above with different colours, in order to identify either cluster of similar regions or peculiar isolated cases. Maps 2a shows that in the first sub-period two big red clusters of highly productive regions which are close to each other arises. One is located in Scandinavia, more precisely in Norway and Sweden; another one is in Central Europe and it goes across several countries from Italy to Denmark. There are also two small clusters in the South of United Kingdom around London and another one among the Scottish regions in the North. Conversely, aggregations of poorly productive regions are typically located in the South of Europe (the Mezzogiorno of Italy, Iberian peninsula and Greece) but also in some Northern regions: Ireland and Finland in particular.
Map 2b describes quite a different scene ten years later. First of all, the central European cluster shrinks to just some regions in Switzerland, Austria and Germany. There is also a small cluster between Belgium and the Netherlands, but all the regions in between are now characterised by the presence of territories with low productivity surrounded by other low productivity regions. In the North of Europe the performance, on the contrary, improves. The Scandinavian cluster increases and Finland has now some regions which have high productivity even though they are still contiguous with low TFP regions. Moreover, the cluster of highly

[24] Similar result have been found in Di Liberto *et al.* (2010) at the country level.
[25] In Table 2A in the appendix more detailed information is given about the Local Indicator of Spatial Association which provides the significance of the relationship for each region and its neighbours (Anselin, 1995).

productive regions in the southern UK almost joins with the one in the North and, most importantly spills over Ireland. At the same time, a dramatic change is observed among the low-TFP cluster regions since the mass of low productivity regions now stretches along the whole of the South of Europe and includes France and many German regions.
The image provided by the comparison of the two maps above is thus worry some: a dual Europe is taking form without the an extensive fringe zone which was guaranteed in the past by central European countries. The risk is that the inertia of spatial association will keep on working in a positive way in the North and mainly in a negative way in the South.

[Map 2 a,b around here]

To further interpret the evolution captured by the analysis of the Moran scatterplot and the Moran maps we introduce an innovative graphic tool called Directional Moran Scatterplot, which is reported in figure 3 below. According to Rey *et al.* (2010) our previous maps "may mask, or even misidentify, individual movements of economies and their neighbours" (p. 5) and the directional scatterplot is thus meant to avoid such a risk.

[Figure 3 around here]

Figure 3 displays the Directional Moran Scatterplot applied to our data in order to pinpoint each region's transitions along time as a vector, where the arrowhead pointing identifies the movement towards the location in the final period. Since a clear visualization of 199 regional transitions is almost impossible, we distinguish between 1) movements within the same quadrant (reported in figure 3a), and 2) movements across quadrants (in figure 3b).
From the first figure we can spot several movements in the LL quadrant of Greek and Portuguese regions upwards: a sign of weak convergence of the least productive regions. In the HH quadrant the most interesting moves are those of Swiss regions which reposition closer to the origin. From the second figure we can easily discern the dramatic change of the two Irish regions moving from the LL quadrant to the HH one together with the opposite path shown by German regions which move in the reverse direction: from the HH to the LL quadrant.

[Table 6 around here]

Another piece of information about the regional TFP dynamic can be found in Table 6 that introduces a standard transition matrix for regional TFP levels as more often done in income distribution studies. Unlike income distribution transition matrix, in this table we consider transitions across the quadrants of the scatterplot over time (see Rey and Ye, 2010). Therefore, the main diagonal include the quota of regions that between the first and the second sub-periods do not change their "state" between HH, LL, HL or LH. We notice that the most stable quadrant is the LL (85% regions keep their position), the least stable is the HL. In this case, it is interesting to note that most regions go from HL to HH so there is a cluster effect referring to HH regions. However this result is in contrast with the fact that almost half regions which were in HH quadrant in the first period have moved going either to HL (19%) or to LL (22%). This implies that some positive spatial dependence among rich regions is now still positive but among poor regions. The strength of this cluster is therefore quite weak. Another interesting aspect illustrated in table 6 is the fact that 35% of those regions which were in the LH quadrant are now in the LL, as if the spatial dependence among poor regions is getting stronger along time.

[Figure 4 here]

Finally, to complete the picture, we introduce our last piece of descriptive analysis suggested by Rey *et al.* (2010), that is, the rose diagram. This diagram is a circular histogram which allows to have a clear, immediate idea of the frequency of moves across different directions. We distinguish 8 possible directions, or circular segments, based on angular motion. From figure 4, thus, we observe that the most frequent direction is upward (the two segments from 0 to 90 degrees) which implies that a region and its neighbours improve their relative TFP position. Nevertheless, figure 4 reveals that that there is no strong spatial integration in the evolution of the regional TFP distribution since movement are quite well spread across the four quadrants. Results show that the most frequent movement is the one which relates to those cases where the region's position improves more than that of neighbours (the segment from 0 to 45 degrees).

6. Conclusions

The main aim of this paper is to assess the existence of technology convergence across a sample of 199 European regions between 1985 and 2006. Different methodologies have been proposed to measure TFP heterogeneity across regions, but only a few of them try to capture the presence of technology convergence as a separate component from the standard (capital-deepening) source of convergence. To distinguish between these two components of convergence, we have proposed and applied a fixed-effect panel methodology. Robustness of results is assessed using different estimation procedures such as simple LSDV, spatially-corrected LSDV, Kiviet-corrected LSDV, and GMM *à la* Arellano and Bond (1991).

Our empirical analysis confirms the presence of a high and persistent level of TFP heterogeneity across regions. Furthermore, we do not find evidence of a global process of TFP convergence, since the dispersion of the estimated TFP levels remained constant through time. Within this aggregate persistence, important changes are nevertheless detected. Such changes have an important geographical component since spatial dependence is proved to be a constant feature of TFP distribution along time. In particular we observe that there is a polarisation of richer regions in the North of Europe while southern regions lose ground in terms of productivity.

In sum, our ample descriptive analysis offers a broad picture, not always reassuring, about TFP dynamics and technology diffusion processes across EU regions. First of all, we find that while the global distribution of regional TFP levels seems to remain quite stable over time, the intra-distribution (or single regions movements) dynamics shows significant ranking changes across regions. More inspection suggest the presence of regional productivity polarisation between high and low TFP levels . This might be the result of a recent asymmetric shock due to the IT revolution that may have affected the various regions in a different way. Overall, results seem to suggest that a few TFP leaders are emerging and are distancing themselves from the rest, while the cluster of low TFP regions is increasing. This calls for new analysis to investigate the reasons of this apparent absence of technology diffusion processes and to investigate what can be done to reverse these processes.

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Table1. Panel Estimations

Sample: 199 regions EU, (1985-2006)
Dependent Variable: Per Capita VA
Observations: 1393

	I	II	III	IV	V	VI	VII
	OLS	LSDV	SEM*	KIVIET	GMM-AB1	GMM-AB2	GMM-AB3
$\tilde{y}_{it-\tau}$	0.977***	0.599***	0.600***	0.742***	0.599***	0.492***	0.557***
	(0.004)	(0.021)	(0.000)	(0.026)	(0.055)	(0.050)	(0.047)
$\tilde{x}_{1,it-\tau}$	-0.005	0.041***	0.051***	0.038***	0.017	0.088***	0.062***
	(0.005)	(0.010)	(0.000)	(0.011)	(0.013)	(0.023)	(0.017)
$\tilde{x}_{2,it-\tau}$	0.011	0.027	-0.010	0.011	0.023	0.008	0.077***
	(0.013)	(0.017)	(0.516)	(0.018)	(0.019)	(0.030)	(0.019)
Spatial Autocorrelation			0.922***				
			(0.000)				
Sargan test (p-value)					0.000	0.000	0.000
AB-2 test (p-value)					0.39	0.11	0.16

*Pooled model with spatial error autocorrelation and spatial fixed effects

Table 2 Spearman's rank correlation coefficient

Estimators	LSDV	SEM	KIVIET	VAP85
LSDV	1.000	0.999	0.996	0.927
SEM		1.000	0.995	0.925
KIVIET			1.000	0.953
VAP85				1.000

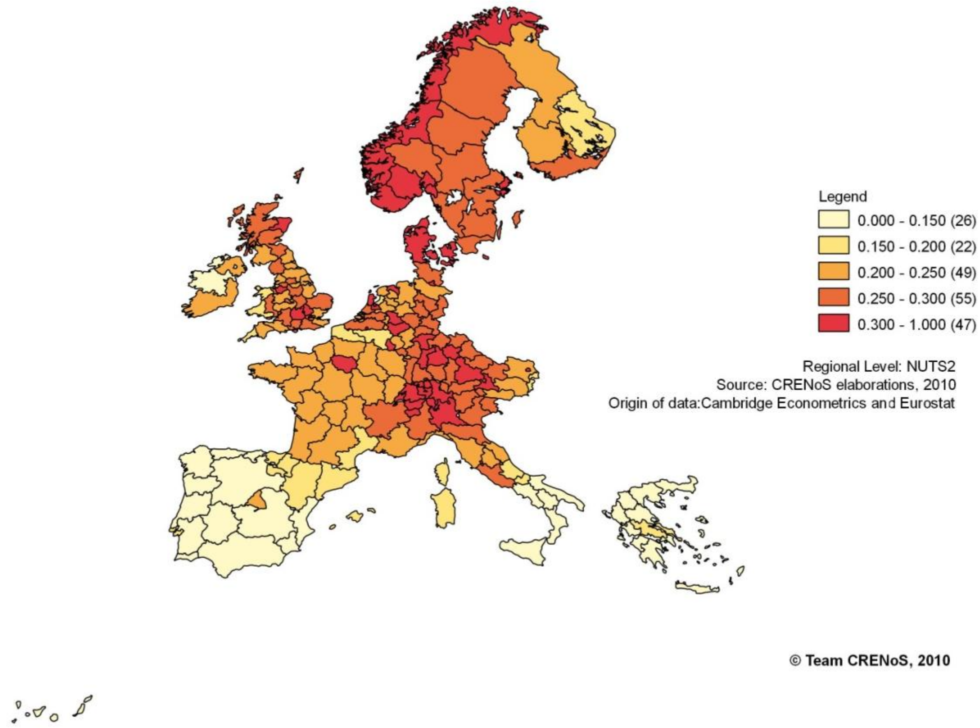
Table3. Panel Estimations

Sample: 199 regions EU, 3 years time-span
Dependent Variable: Per capita VA
Observations: 796

	1985-1997			1997-2006		
	OLS	LSDV	KIVIET	OLS	LSDV	KIVIET
$\tilde{y}_{it-\tau}$	0.973***	0.231***	0.378***	0.985***	0.649***	0.881***
	(0.006)	(0.032)	(0.042)	(0.004)	(0.029)	(0.038)
$\tilde{x}_{1,it-\tau}$	-0.013	0.018	0.020	0.001	0.035***	0.024***
	(0.007)	(0.019)	(0.019)	(0.005)	(0.011)	(0.011)
$\tilde{x}_{2,it-\tau}$	0.012	0.067***	0.072***	-0.032**	0.086***	-0.095***
	(0.019)	(0.023)	(0.024)	(0.013)	(0.020)	(0.022)

Map1. TFP levels

a) 1985-1997



b) 1997-2006

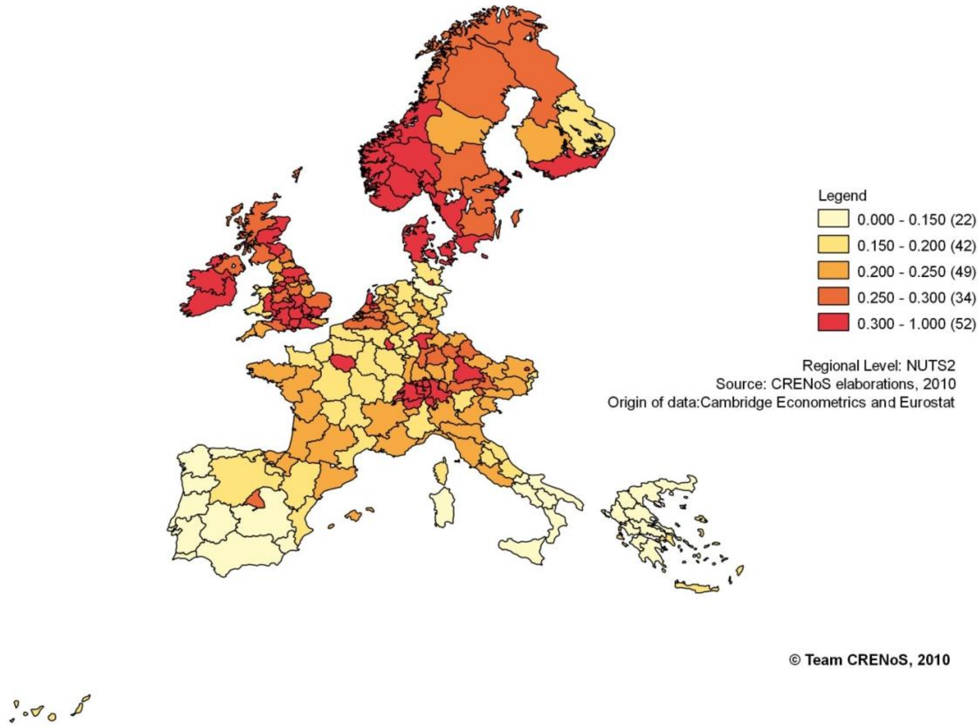


Table 4. CV and Theil index statistics

Periods	Index	
	CV	Theil
1985-1997	0.446	0.088
1994-2006	0.546	0.102

Figure 1. Kernel TFP

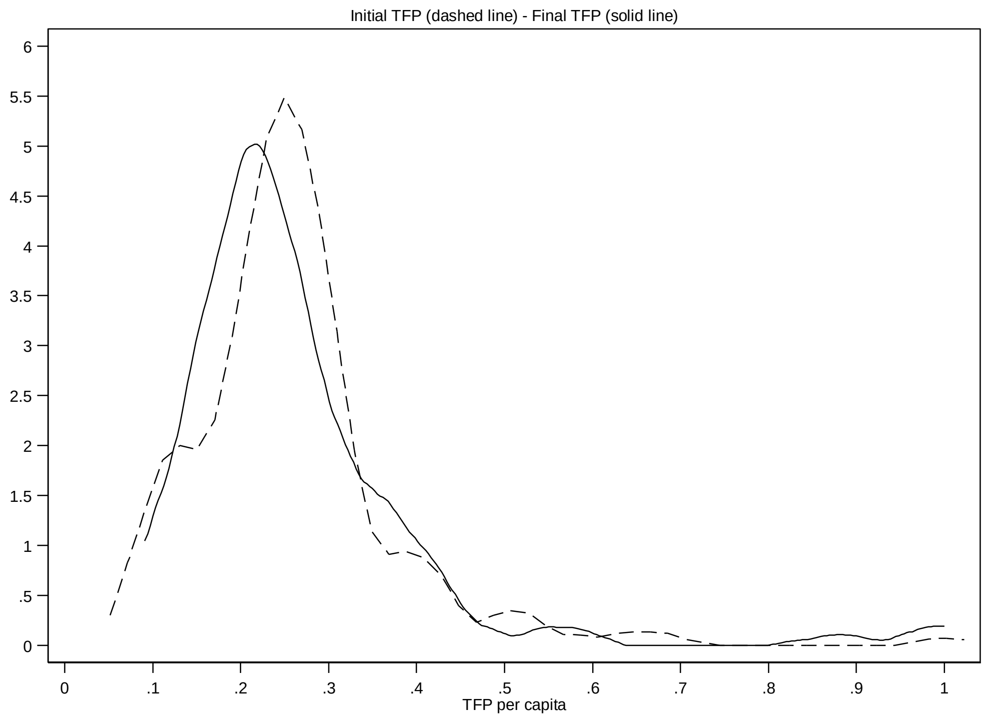
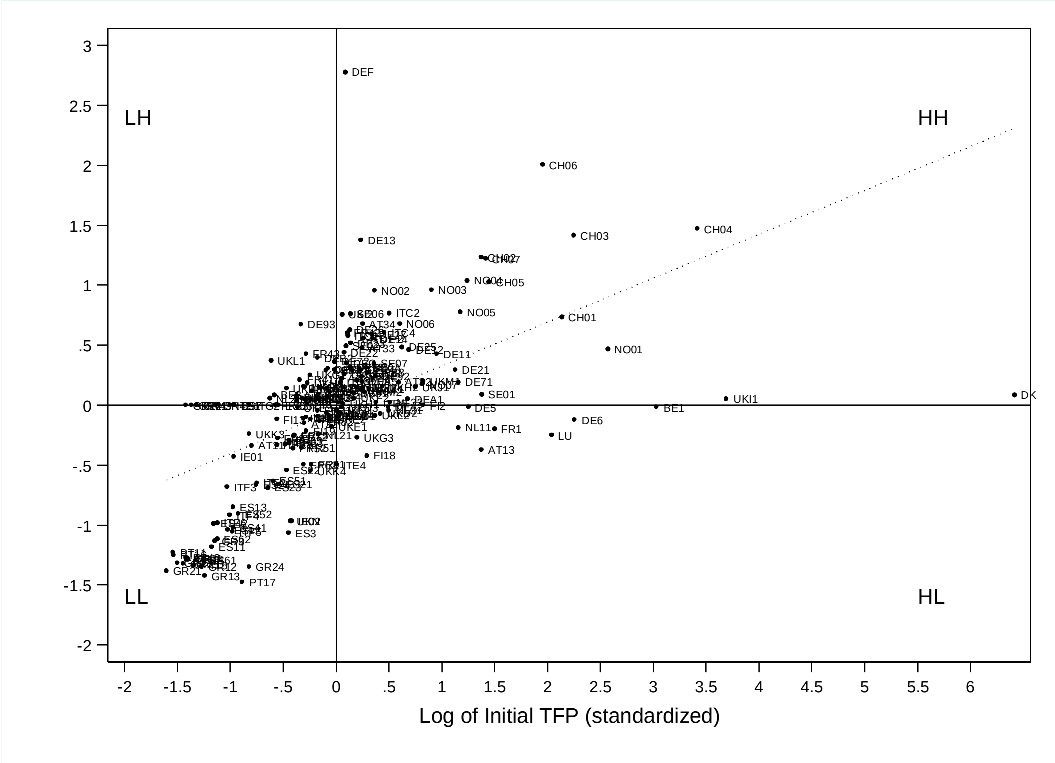


Figure 2. Moran Scatterplot for per capita TFP

a) **1985-1997**



b) **1997-2006**

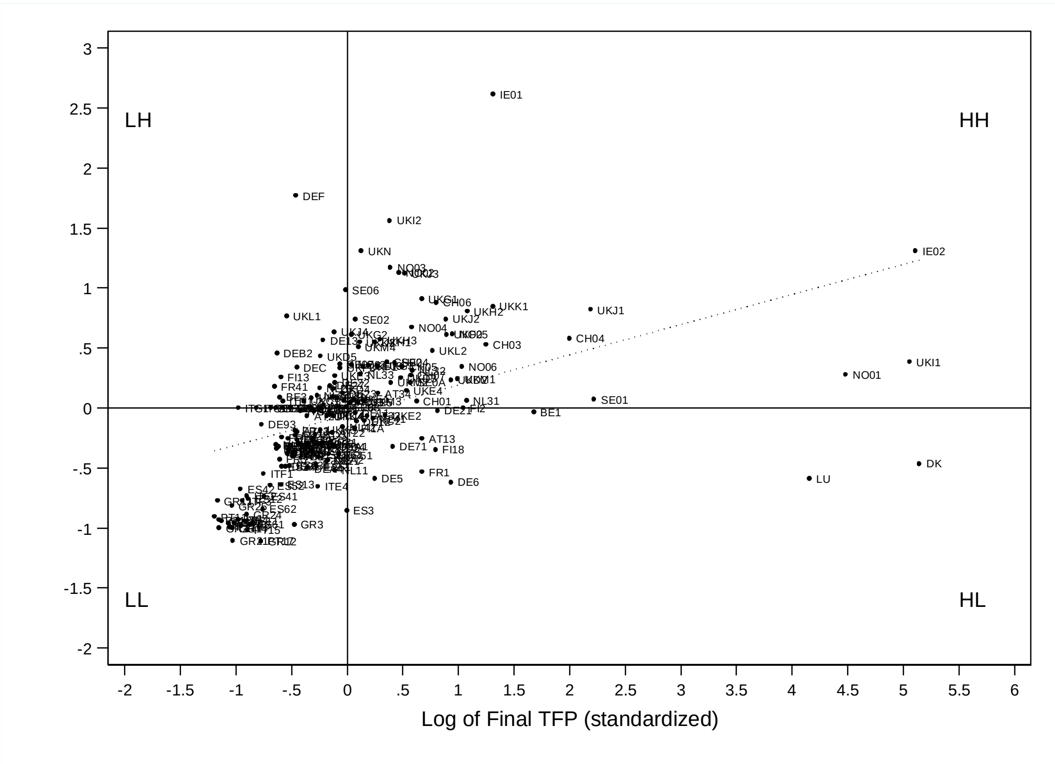
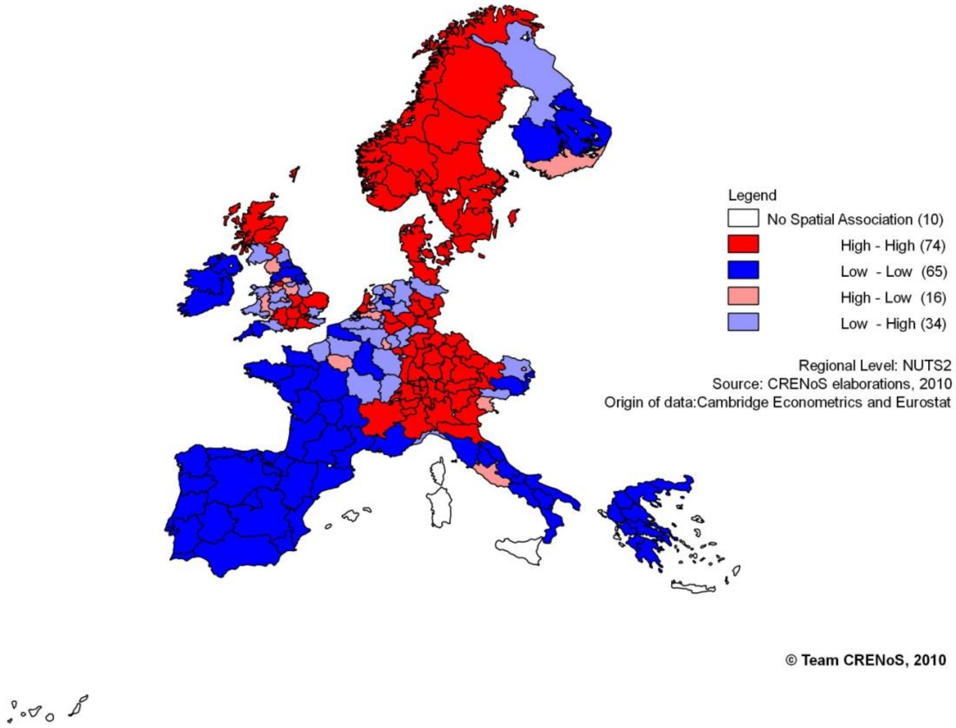


Table 5. Spatial Association in the Moran Scatterplot

	Quadrant HH	Quadrant LL	Quadrant HL	Quadrant LH	No Quadrant
	%	%	%	%	%
1985-1997	0.37	0.33	0.08	0.17	0.05
1994-2006	0.28	0.43	0.07	0.18	0.05

Map 2. Moran maps

a) 1985-1997



b) 1997-2006

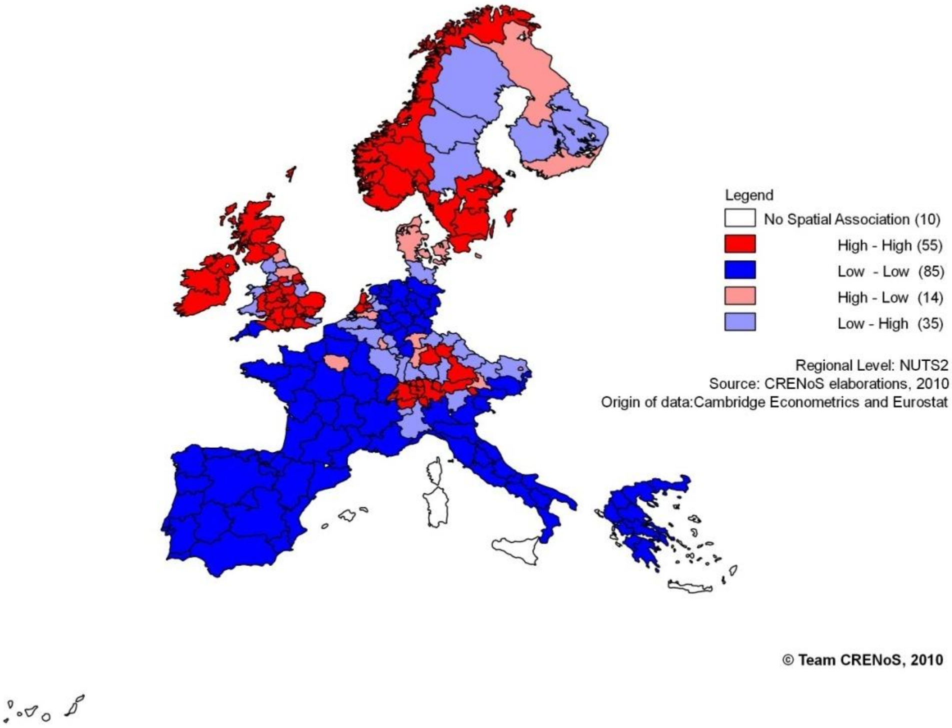
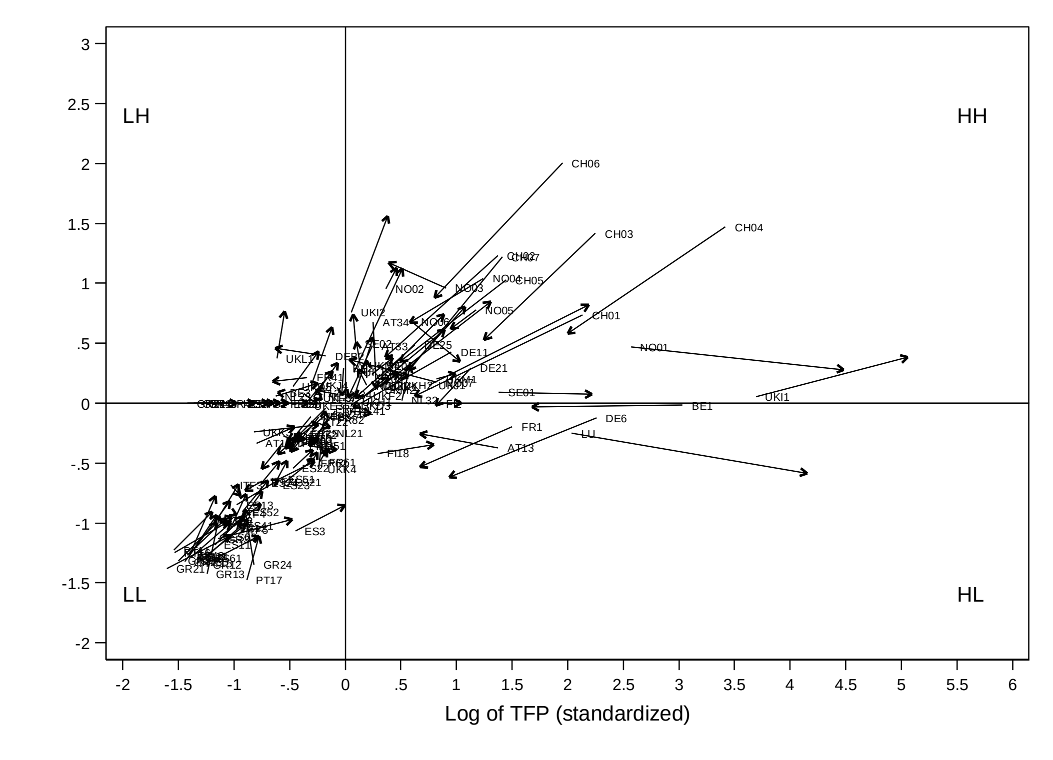

Legend
No Spatial Association (10)
High - High (55)
Low - Low (85)
High - Low (14)
Low - High (35)
Regional Level: NUTS2
Source: CRENoS elaborations, 2010
Origin of data:Cambridge Econometrics and Eurostat
© Team CRENoS, 2010

Figure 3. Directional Moran Scatterplot

- **a) Regions which do not change quadrant**



- **b) Regions which change quadrant**

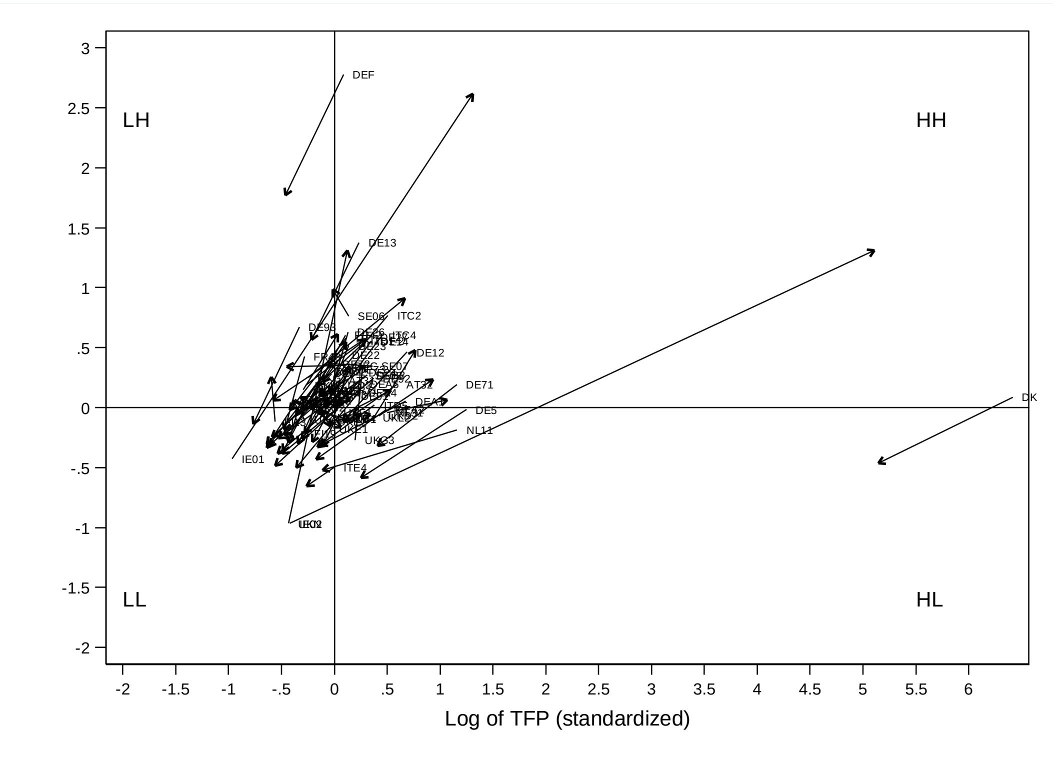
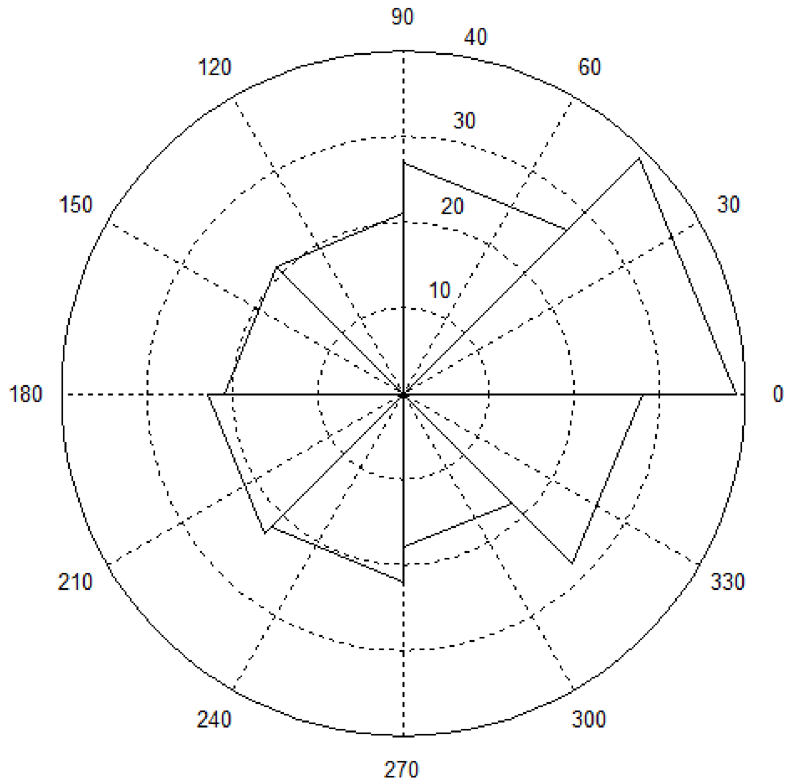


Table 6. Transition matrix in the Moran Scatterplot

	(1994-2006)			
(1985-1997)	Quadrant HH	Quadrant LL	Quadrant HL	Quadrant LH
Quadrant HH	54.05%	16.22%	6.76%	22.97%
Quadrant LL	6.15%	86.15%	1.54%	6.15%
Quadrant HL	37.50%	18.75%	37.50%	6.25%
Quadrant LH	14.71%	41.18%	5.88%	38.24%

Figure 4. Rose Diagram: Moran Movement Vector



APPENDIX

Table A1

cod_reg	name_reg	TFP 1985-06	VAPC85	TFP 1985-97	TFP 1997-06	var. ranking
ES22	Navarra	145	154	148	114	34
ES23	Rioja	160	158	160	146	14
ES24	Aragon	162	166	162	157	5
ES3	Madrid	136	156	146	71	75
ES41	Castilla-Leon	171	174	171	171	0
ES42	Castilla-la Mancha	183	186	182	186	-4
ES43	Extremadura	192	194	194	194	0
ES51	Cataluna	151	162	157	111	46
ES52	Com. Valenciana	170	167	168	170	-2
ES53	Baleares	155	153	151	121	30
ES61	Andalucia	184	188	185	178	7
ES62	Murcia	180	181	178	173	5
ES7	Canarias	172	176	169	155	14
FI13	Ita-Suomi	152	150	154	158	-4
FI18	Etela-Suomi	40	51	51	25	26
FI19	Lansi-Suomi	113	110	121	81	40
FI1A	Pohjois-Suomi	121	127	137	66	71
FI2	Aland	24	25	25	15	10
FR1	Ile de France	13	15	11	27	-16
FR21	Champagne-Ard.	115	113	110	151	-41
FR22	Picardie	143	125	136	164	-28
FR23	Haute-Normandie	105	87	100	136	-36
FR24	Centre	116	103	109	130	-21
FR25	Basse-Normandie	146	139	139	145	-6
FR26	Bourgogne	124	109	108	156	-48
FR3	Nord-Pas de Calais	150	140	149	161	-12
FR41	Lorraine	141	130	134	168	-34
FR42	Alsace	90	76	74	115	-41
FR43	Franche-Comte	132	123	124	135	-11
FR51	Pays de la Loire	125	132	132	80	52
FR52	Bretagne	139	141	141	105	36
FR53	Poitou-Charentes	144	143	145	125	20
FR61	Aquitaine	117	105	114	95	19
FR62	Midi-Pyrenees	129	129	129	107	22
FR63	Limousin	148	148	144	148	-4
FR71	Rhone-Alpes	87	81	80	100	-20
FR72	Auvergne	142	144	140	140	0
FR81	Languedoc-Rouss.	153	151	152	127	25
FR82	?rov-Alpes-Cote d'Azu	107	98	106	117	-11
FR83	Corse	154	147	155	143	12
GR11	Anatoliki Makedonia	195	180	191	198	-7
GR12	Kentriki Makedonia	186	184	186	175	11
GR13	Dytiki Makedonia	188	183	184	195	-11
GR14	Thessalia	191	190	190	191	-1
GR21	Ipeiros	199	195	199	190	9
GR22	Ionia Nisia	190	192	193	169	24
GR23	Dytiki Ellada	196	193	196	196	0
GR24	Sterea Ellada	165	146	164	182	-18
GR25	Peloponnisos	193	187	195	192	3
GR3	Attiki	173	179	181	137	44
GR41	Voreio Aigaio	187	191	189	144	45
GR42	Notio Aigaio	179	182	180	142	38
GR43	Kriti	185	189	187	167	20
IE01	Border	158	175	170	10	160

cod_reg	name_reg	TFP 1985-06	VAPC85	TFP 1985-97	TFP 1997-06	var. ranking
IE02	Southern and Eastern	47	159	142	2	140
ITC1	Piemonte	91	82	73	128	-55
ITC2	Valle d'Aosta	52	34	35	102	-67
ITC3	Liguria	101	117	105	122	-17
ITC4	Lombardia	49	47	38	88	-50
ITD1-2	Trentino-Alto Adige	111	57	54	154	-100
ITD3	Veneto	97	95	86	113	-27
ITD4	Friuli-Venezia Giulia	85	96	89	84	5
ITD5	Emilia-Romagna	59	44	41	94	-53
ITE1	Toscana	100	111	101	120	-19
ITE2	Umbria	138	131	130	147	-17
ITE3	Marche	128	133	116	138	-22
ITE4	Lazio	89	94	90	109	-19
ITF1	Abruzzo	159	149	153	172	-19
ITF2	Molise	166	161	161	181	-20
ITF3	Campania	178	170	177	184	-7
ITF4	Puglia	176	172	175	187	-12
ITF5	Basilicata	177	168	173	185	-12
ITF6	Calabria	181	178	179	189	-10
ITG1	Sicilia	175	173	174	188	-14
ITG2	Sardegna	167	164	165	177	-12
LU	LUXEMBOURG	6	12	9	5	4
NL11	Groningen	25	2	20	83	-63
NL12	Friesland	135	142	131	129	2
NL13	Drenthe	131	66	103	166	-63
NL21	Overijssel	108	136	107	98	9
NL22	Gelderland	119	135	115	99	16
NL23	Flevoland	161	160	159	106	53
NL31	Utrecht	29	68	36	14	22
NL32	Noord-Holland	34	33	34	31	3
NL33	Zuid-Holland	60	74	65	59	6
NL34	Zeeland	102	101	99	110	-11
NL41	Noord-Brabant	73	107	85	52	33
NL42	Limburg (NL)	99	126	112	75	37
NO01	Oslo og Akershus	4	7	5	4	1
NO02	Hedmark og Oppland	43	37	44	39	5
NO03	Sor-Ostlandet	27	16	24	43	-19
NO04	Agder og Rogaland	23	9	18	32	-14
NO05	Vestlandet	21	14	19	18	1
NO06	Trondelag	28	31	32	16	16
NO07	Nord-Norge	32	19	27	69	-42
PT11	Norte	198	199	198	199	-1
PT15	Algarve	189	196	188	180	8
PT16	Centro (P)	197	198	197	193	4
PT17	Lisboa	168	177	167	176	-9

cod_reg	name_reg	TFP 1985-06	VAPC85	TFP 1985-97	TFP 1997-06	var. ranking
PT18	Alentejo	194	197	192	197	-5
SE01	Stockholm	11	17	14	6	8
SE02	Ostra Mellansverige	69	62	76	64	12
SE04	Sydsverige	45	53	59	40	19
SE06	Norra Mellansverige	65	64	69	73	-4
SE07	Mellersta Norrland	44	40	45	78	-33
SE08	Ovre Norrland	50	41	50	72	-22
SE09	Smaland med oarna	55	55	64	53	11
SE0A	Vastsverige	41	48	52	34	18
UKC1	Tees Valley and Durham	134	115	123	126	-3
UKC2	Northumberland and Tyne and Wear	103	114	119	55	64
UKD1	Cumbria	95	71	87	119	-32
UKD2	Cheshire	37	58	40	20	20
UKD3	Greater Manchester	61	73	83	38	45
UKD4	Lancashire	92	99	97	87	10
UKD5	Merseyside	140	121	147	103	44
UKE1	East Riding and North Lincolnshire	88	106	94	67	27
UKE2	North Yorkshire	81	102	96	46	50
UKE3	South Yorkshire	123	112	135	85	50
UKE4	West Yorkshire	64	90	88	35	53
UKF1	Derbyshire and Nottinghamshire	80	84	91	57	34
UKF2	Leicestershire, Rutland and Northamptonsh	48	70	66	21	45
UKF3	Lincolnshire	127	134	125	77	48
UKG1	Herefordshire, Worcestershire and Warwic	94	138	118	29	89
UKG2	Shropshire and Staffordshire	112	128	126	68	58
UKG3	West Midlands	56	72	63	49	14
UKH1	East Anglia	75	86	81	51	30
UKH2	Bedfordshire and Hertfordshire	31	46	39	13	26
UKH3	Essex	104	124	120	47	73
UKI1	Inner London	2	3	2	3	-1
UKI2	Outer London	72	104	82	44	38
UKJ1	Berkshire, Buckinghamshire and Oxfordshi	18	38	28	7	21
UKJ2	Surrey, East and West Sussex	42	83	56	22	34
UKJ3	Hampshire and Isle of Wight	62	85	78	36	42
UKJ4	Kent	126	137	128	86	42
UKK1	Gloucestershire, Wiltshire and North Somer	36	69	48	11	37
UKK2	Dorset and Somerset	106	119	122	60	62
UKK3	Cornwall and Isles of Scilly	164	165	166	104	62
UKK4	Devon	122	118	117	97	20
UKL1	West Wales and The Valleys	157	157	158	152	6
UKL2	East Wales	38	60	42	26	16
UKM1	North Eastern Scotland	22	59	26	17	9
UKM2	Eastern Scotland	51	56	53	42	11
UKM3	South Western Scotland	93	116	104	56	48
UKM4	Highlands and Islands	58	92	70	61	9
UKN	Northern Ireland	133	145	143	58	85

Table A2

Code	Regions	KIVIET (1985-1997)	KIVIET (1994-2006)
AT11	Burgenland	LL	LL
AT12	Niederosterreich	LH	LH
AT13	Wien	HL	HL
AT21	Karnten	LH	LL
AT22	Steiermark	LL	LL
AT31	Oberosterreich	HH	LH
AT32	Salzburg	HH	HL
AT33	Tirol	HH	HH
AT34	Vorarlberg	HH	HH
BE1	Bruxelles-Brussel	HH	HH
BE2	Vlaams Gewest	LH	LH
BE3	Region Walonne	LH	LH
CH01	Region Lemanique	HH***	HH
CH02	Espace Mittelland	HH***	HH
CH03	Nordwestschweiz	HH***	HH
CH04	Zurich	HH***	HH**
CH05	Ostschweiz	HH***	HH
CH06	Zentralschweiz	HH***	HH*
CH07	Ticino	HH***	HH
DE11	Stuttgart	HH	HH
DE12	Karlsruhe	HH	HL
DE13	Freiburg	HH	LH
DE14	Tubingen	HH	LH
DE21	Oberbayern	HH	HH
DE22	Niederbayern	HH	LH
DE23	Oberpfalz	HH	LH
DE24	Oberfranken	HH	LH
DE25	Mittelfranken	HH	HH
DE26	Unterfranken	HH	LH
DE27	Schwaben	HH	LH
DE5	Bremen	HH	HL
DE6	Hamburg	HL	HL
DE71	Darmstadt	HH	HL
DE72	Giessen	LH	LL
DE73	Kassel	HH	LL
DE91	Braunschweig	HH	LL
DE92	Hannover	HH	LL
DE93	Luneburg	LH	LL
DE94	Weser-Ems	LH	LL
DEA1	Dusseldorf	HH	LL
DEA2	Koln	HH	LL
DEA3	Munster	LH	LL
DEA4	Detmold	HH	LL
DEA5	Arnsberg	HH	LL
DEB1	Koblenz	LH	LL
DEB2	Trier	LH	LH
DEB3	Rheinhessen-Pfalz	HH	LL
DEC	Saarland	HH	LH
DEF	Schleswig-Holstein	HH	LH
DK	DENMARK	HH	HL**

Code	Regions	KIVIET (1985-1997)	KIVIET (1994-2006)
ES11	Galicia	LL***	LL
ES12	Asturias	LL*	LL
ES13	Cantabria	LL	LL
ES21	Pais Vasco	LL	LL
ES22	Navarra	LL	LL
ES23	Rioja	LL	LL
ES24	Aragon	LL	LL
ES3	Madrid	LL	LL
ES41	Castilla-Leon	LL***	LL*
ES42	Castilla-la Mancha	LL***	LL*
ES43	Extremadura	LL***	LL**
ES51	Cataluna	LL	LL
ES52	Com. Valenciana	LL*	LL
ES53	Baleares	No Association	No Association
ES61	Andalucia	LL***	LL**
ES62	Murcia	LL**	LL
ES7	Canarias	No Association	No Association
FI13	Ita-Suomi	LL	LH
FI18	Etela-Suomi	HL	HL
FI19	Lansi-Suomi	LL	LH
FI1A	Pohjois-Suomi	LH	HL
FI2	Aland	No Association	No Association
FR1	Ile de France	HL	HL
FR21	Champagne-Ard.	LL	LL
FR22	Picardie	LH	LL
FR23	Haute-Normandie	LH	LL
FR24	Centre	LL	LL
FR25	Basse-Normandie	LL	LL
FR26	Bourgogne	LH	LL
FR3	Nord-Pas de Calais	LL	LL
FR41	Lorraine	LH	LH
FR42	Alsace	HH	LH
FR43	Franche-Comte	LH	LL
FR51	Pays de la Loire	LL	LL
FR52	Bretagne	LL	LL
FR53	Poitou-Charentes	LL	LL
FR61	Aquitaine	LL	LL
FR62	Midi-Pyrenees	LL	LL
FR63	Limousin	LL	LL
FR71	Rhone-Alpes	HH	LL
FR72	Auvergne	LL	LL
FR81	Languedoc-Rouss.	LL	LL
FR82	Prov-Alpes-Cote d'Azur	LL	LL
FR83	Corse	No Association	No Association
GR11	Anatoliki Makedonia	LL*	LL
GR12	Kentriki Makedonia	LL***	LL
GR13	Dytiki Makedonia	LL***	LL*
GR14	Thessalia	LL***	LL**
GR21	Ipeiros	LL***	LL**
GR22	Ionia Nisia	No Association	No Association

Code	Regions	KIVIET (1985-1997)	KIVIET (1994-2006)
GR23	Dytiki Ellada	LL***	LL**
GR24	Sterea Ellada	LL**	LL
GR25	Peloponnisos	LL***	LL
GR3	Attiki	LL*	LL
GR41	Voreio Aigaio	No Association	No Association
GR42	Notio Aigaio	No Association	No Association
GR43	Kriti	No Association	No Association
IE01	Border	LL	HH***
IE02	Southern and Eastern	LL	HH***
ITC1	Piemonte	HH	LH
ITC2	Valle d'Aosta	HH	LH
ITC3	Liguria	LH	LL
ITC4	Lombardia	HH	LL
ITD1-2	Trentino-Alto Adige	HH	LH
ITD3	Veneto	HH	LL
ITD4	Friuli-Venezia Giulia	HL	LL
ITD5	Emilia-Romagna	HH	LL
ITE1	Toscana	LL	LL
ITE2	Umbria	LL	LL
ITE3	Marche	LL	LL
ITE4	Lazio	HL	LL
ITF1	Abruzzo	LL	LL
ITF2	Molise	LL	LL
ITF3	Campania	LL	LL
ITF4	Puglia	LL*	LL*
ITF5	Basilicata	LL*	LL*
ITF6	Calabria	LL	LL
ITG1	Sicilia	No Association	No Association
ITG2	Sardegna	No Association	No Association
LU	LUXEMBOURG	HL	HL***
NL11	Groningen	HL	LL
NL12	Friesland	LH	LL
NL13	Drenthe	LH	LL
NL21	Overijssel	LL	LL
NL22	Gelderland	LH	LH
NL23	Flevoland	LH	LH
NL31	Utrecht	HL	HH
NL32	Noord-Holland	HH	HH
NL33	Zuid-Holland	HH	HH
NL34	Zeeland	LH	LH
NL41	Noord-Brabant	HL	HL
NL42	Limburg (NL)	LH	LL
NO01	Oslo og Akershus	HH**	HH**
NO02	Hedmark og Oppland	HH	HH
NO03	Sor-Ostlandet	HH**	HH
NO04	Agder og Rogaland	HH*	HH
NO05	Vestlandet	HH*	HH
NO06	Trondelag	HH	HH
NO07	Nord-Norge	HH	HH
PT11	Norte	LL***	LL**

Code	Regions	KIVIET (1985-1997)	KIVIET (1994-2006)
PT15	Algarve	LL***	LL
PT16	Centro (P)	LL***	LL**
PT17	Lisboa	LL*	LL
PT18	Alentejo	LL***	LL**
SE01	Stockholm	HH	HH
SE02	Ostra Mellansverige	HH	HH
SE04	Sydsverige	HH	HH
SE06	Norra Mellansverige	HH	LH
SE07	Mellersta Norrland	HH	LH
SE08	Ovre Norrland	HH	LH
SE09	Smaland med oarna	HH	HH
SE0A	Vastsverige	HH	HH
UKC1	Tees Valley and Durham	LL	LH
UKC2	Northumberland and Tyne and Wear	LH	HL
UKD1	Cumbria	HL	LH
UKD2	Cheshire	HL	HH
UKD3	Greater Manchester	HH	HH
UKD4	Lancashire	LL	LH
UKD5	Merseyside	LH	LH
UKE1	East Riding and North Lincolnshire	LL	HH
UKE2	North Yorkshire	LL	HL
UKE3	South Yorkshire	LH	LH
UKE4	West Yorkshire	HL	HH
UKF1	Derbyshire and Nottinghamshire	HL	HH
UKF2	Leicestershire	HH	HH
UKF3	Lincolnshire	LH	LH
UKG1	Herefordshire	LH	HH
UKG2	Shropshire and Staffordshire	LH	HH
UKG3	West Midlands	HL	HH
UKH1	East Anglia	HH	HH
UKH2	Bedfordshire and Hertfordshire	HH	HH**
UKH3	Essex	LH	HH
UKI1	Inner London	HH	HH**
UKI2	Outer London	HH	HH
UKJ1	Berkshire	HH	HH***
UKJ2	Surrey	HH	HH
UKJ3	Hampshire and Isle of Wight	HH	HH
UKJ4	Kent	LH	LH
UKK1	Gloucestershire	HH	HH***
UKK2	Dorset and Somerset	LH	HH
UKK3	Cornwall and Isles of Scilly	LL	LL
UKK4	Devon	LL	LL
UKL1	West Wales and The Valleys	LH	LH
UKL2	East Wales	HL	HH
UKM1	North Eastern Scotland	HH	HH
UKM2	Eastern Scotland	HH	HH
UKM3	South Western Scotland	LH	HH
UKM4	Highlands and Islands	HH	HH
UKN	Northern Ireland	LL	HH

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Finito di stampare nel mese di Gennaio 2011
Presso **studiografico&stampadigitale Copy Right**
Via Torre Tonda 8 – Tel. 079.200395 – Fax 079.4360444
07100 Sassari

www.crenos.it

ISBN 978-88-84-67-633-7

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