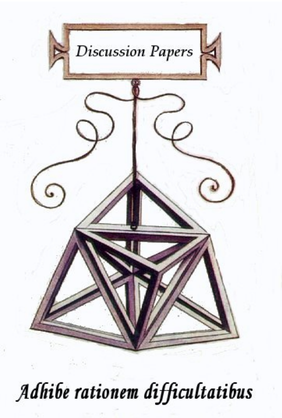
Discussion Papers
Collana di
E-papers del Dipartimento di Economia e Management – Università di Pisa



Davide Fiaschi - Lisa Gianmoena - Angela Parenti

Spatial Clubs in European Regions

Discussion Paper n. 196

2015

Discussion Paper n. 196: **January 2015**

Indirizzo dell'Autore:
Dipartimenti di Economia e Managament
University of Pisa

Please use the following citation:
Fiaschi, D. L. Gianmoena, and A. Parenti (2015), "Local Directional Moran Scatter Plot - LDMS", Discussion Papers of Dipartimento di Economia e Management – University of Pisa, n. 196 (http://www.ec.unipi.it/ricerca/discussion-papers.html).

Discussion Paper
n. 196

Davide Fiaschi - Lisa Gianmoena - Angela Parenti

Abstract

This paper finds evidence of spatial clubs in a sample of 254 European regions in the period 1991-2008. A dynamic extension of the Moran scatter plot, consisting in a non parametric estimate of the joint dynamics of GDP per worker and its spatial lag, suggests the emergence of three spatial clubs: one populated by regions belonging to the former Eastern Bloc countries, one by regions of PIGS countries (Portugal, Italy, Greece and Spain) and the last one by regions of other EU countries (notably Germany, France, UK and Northern Europe countries). In the long run the convergence process is evident only to two spatial clubs with Eastern regions converging to PIGS regions. Spatial spillovers are present across European regions, and their contribution to the emergence of spatial clubs is crucial. On the contrary, cross-region heterogeneity in human capital has a very limited impact on the distribution of GDP per worker. Finally, unobserved heterogeneity explains a substantial share of inequality and polarization.

Classificazione JEL: C21, R11, O52, F41
Keywords: Moran scatter plot, spatial panels, spatial spillovers, bipolarization, core-periphery pattern

Contents

I. Introduction

This paper analyses the emergence of spatial clubs in a sample of 254 European regions in the period 1991-2008, and estimate the contribution of spatial spillovers (SS) to this spatial pattern.[1]

Figures 1 and 2 provide the starting point of the analysis.[2]

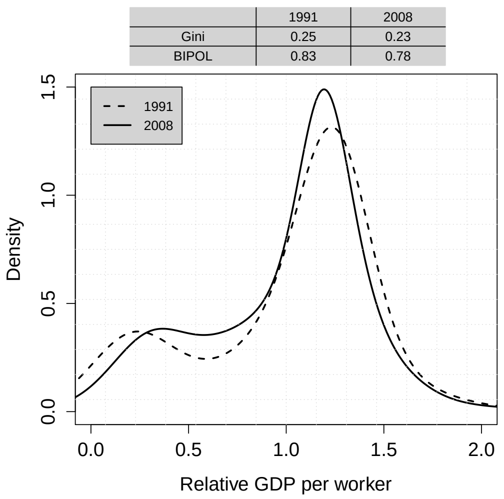


Figure 1: Estimated distributions of (relative) GDP per worker in 1991 and 2008 of 254 NUTS-2 European regions.

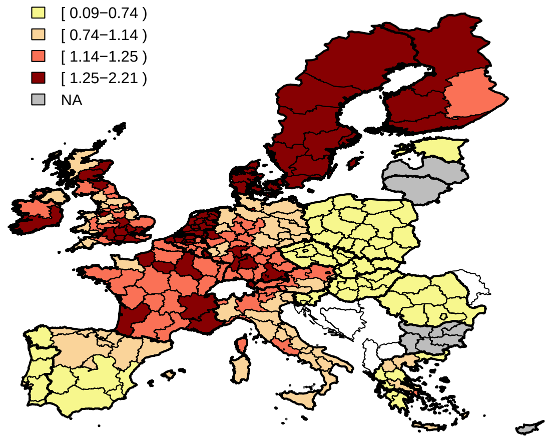


Figure 2: Spatial patterns of (relative) GDP per worker in 2008 of 254 NUTS-2 European regions.

The estimated densities in 1991 and 2008 reveal the presence of a stable twin-peaked distribution. Gini and BIPOL (bipolarization) indexes of GDP per worker distribution point to a slightly decrease both in dispersion and polarization in the period, although polarization remains very high in the last year.[3]

Figure 2 provides a picture of the spatial pattern in 2008: a cluster of regions at the core of Europe with relatively high levels of GDP per worker are contrasted by a cluster of regions at the southern borders of Europe with a medium GDP per worker, belonging to so-called PIGS countries (Portugal, Italy, Greece and Spain); and by a cluster of regions at the eastern borders with a low GDP per worker, belonging to the countries of former Eastern Bloc. Regions of countries not belonging to EMU (Denmark, Sweden, and UK) do not show any specific

[1]See Appendix C for the regions list.

[2]Density estimations are made by an adaptive kernel estimator with optimal normal bandwidth (see Fiaschi and Romanelli, 2009 for more details).

[3]BIPOL is defined in the range $[0, 1]$, with 1 representing maximum polarization (see Anderson et al., 2012 for more details).

pattern with respect of the regions of high-per-worker GDP cluster. The core-periphery theory seems to find a further confirm (see Fujita et al., 1999), and the emerge of spatial clubs is confirmed. Spatial clubs are therefore defined as spatial clusters of regions with similar levels of GDP per workers.

II. Spatial Clubs in European Regions

The starting point to identify the emergence of spatial clubs is the Moran scatter plot. The advantage of Moran scatter plot is its easy interpretation giving a graphical representation of the relation of the variable, in our case the (relative) GDP per worker in the location j with respect the values of that variable in the neighbouring locations, i.e the spatial lag variable. Figure 3 depicted the Moran scatter plot for the initial year (1991). X-axis reports the (relative) GDP per worker, y, while y-axis reports its spatial lag, $W\mathbf{y}$ ($\mathbf{y}$ is the vector of GDP per worker of all regions in the sample). [4]

The Moran's I [5] test in 1991 is positive (equal to 0.764) and statistically significant at 10%, suggesting the presence of spatial dependence. Moreover, the distribution in 1991 appears characterized by three spatial clubs of regions (indicated by three yellow circles identified by a *k-median* algorithm [6]), where spatial clubs should be meant in this case, as clusters of regions with similar levels both of GDP per worker y and spatially lagged GDP per worker $W\mathbf{y}$.[7] These three clubs of regions have a clear correspondence with the spatial pattern

[4]The spatial lag of GDP per worker for region i, $W_i\mathbf{y}$, consists in the average value of GDP per worker of neighbours of region i (under the assumption that W is row-standardized). W is the *spatial matrix*, see A for more details. We control that our results are robust to alternative definition of W, as the first-order and second-order contiguity.

[5]Moran's I is a measure of spatial autocorrelation, and tell us how related the values of a variable are based on the location where they are measured and respect to the values of the nearby locations. In particular, the Moran's I measures the global spatial autocorrelation, that is the overall spatial clustering of the data. It is given by:

$$I = \frac{\frac{N}{S_0}\sum_i \sum_j w_{ij} Z_i Z_j}{\sum_i Z_i^2} \tag{1}$$

where Z_i is the deviation of the variable of interest from its mean (GRV_i), w_{ij} are the spatial weights capturing the potential spatial interaction which are different from zero if regions i and j are neighbors (according to some distance measure), N is the number of regions and $S_0 = \sum_i \sum_j w_{ij}$ (when the W matrix of spatial weights is row-standardized $S_0 = N$). The Moran's I statistic takes value $-1 \leq I \leq 1$ ($I = -1$ indicates a strong *negative* spatial autocorrelation, $I = 0$ no spatial autocorrelation, and $I = 1$ a strong *positive* spatial autocorrelation).

[6]The *k-median* algorithm is a variation of *k-means* algorithm where instead of calculating the mean for each cluster to determine its centroid, it is use its median. The use of median should minimize the impact of possible outliers. See Leisch, 2006 for more details on *k-median* algorithm.

[7]In the identification of clubs we have imposed that their number is equal to three on the base of the visual inspection of Figure 3.

displayed in Figure 2 [8], that is C1 corresponds to regions belonging to former Eastern Bloc countries, C2 to regions belonging to PIGS countries, and C3 to regions belonging to other EU countries.

However, the standard Moran scatter plot in Figure 3 does not provide any information on the dynamics of these three spatial clubs. To fill this gap, we estimate the joint dynamics of (relative) GDP per worker y and its spatially lagged $W\mathbf{y}$ over the period 1991-2008 in the Moran space, which we label *Local Directional Moran Scatter Plot* (LDMS) (see Fiaschi et al., 2014).

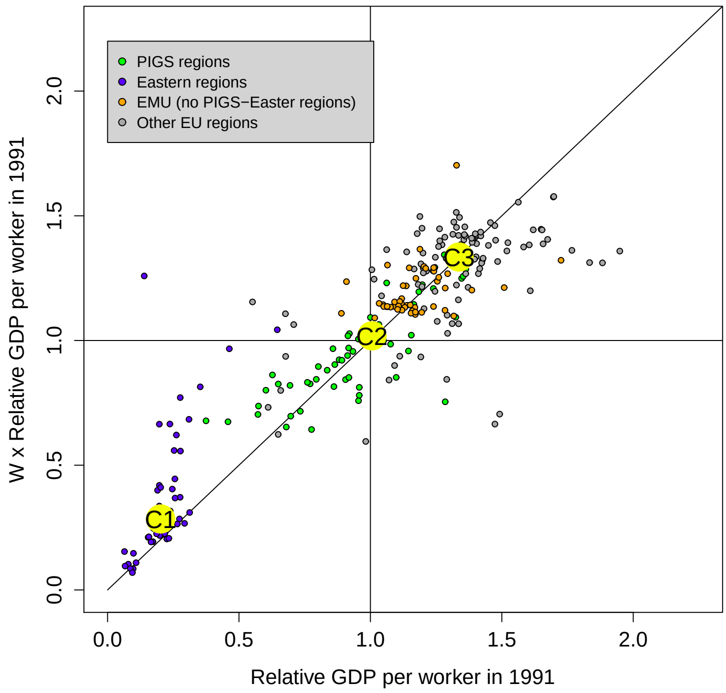


Figure 3: Moran scatter plot for 1991 with the indication of three spatial clubs. The centres of three clubs of regions in 1991 are identified by *k-median* algorithm, and they are indicated by three yellow circles.

II.A. Estimation of a Local Directional Moran Scatterplot

Consider a sample of N economies observed for T periods; economy j is characterized by its level of relative (to the sample average) income in each point in time y_{jt}, and by the average income of its neighbours Wy_{jt}, where W is the j-the row of the spatial weight matrix expressing which economies are neighbours

[8] We report just the geographical distribution in the last year 2008. Similar geographical pattern is found in 1991.

of j ($j = 1, ..., N$ and $t = 1, ..., T$), and y_t is the vector of relative income of all economies.

We assume that the spatial dynamics of economy j at period t, i.e. the dynamics of economy j in the space (y, Wy), only depends on (y_{jt}, Wy_{jt}), i.e. y_{jt} follows a *time invariant* and *Markovian* stochastic process.

The spatial dynamics of the sample in the Moran space can be therefore represented by a random vector field (RVF). In particular, given a subset L of the possible realization of (y, Wy) (i.e. a lattice in the Moran space), a RVF is represented by a random variable $\Delta_\tau z_i$, where $\Delta_\tau z_i \equiv (\Delta_\tau y_i, \Delta_\tau W y_i) \equiv (y_{it+\tau} - y_{it}, W y_{it+\tau} - W y_{it})$, indicating the spatial dynamics (i.e. the dynamics from period t to period $t + \tau$ represented by a movement vector) at $z_i \equiv (y_i, W y_i) \in L$.

For each point in the lattice z_i, with $i = 1, ..., L$, we therefore estimate the distribution of probability $\Pr(\Delta_\tau z | z_i)$ on the $N(T - \tau)$ observed movement vectors $\Delta_\tau^{OBS} z$. In particular, $\Pr\left(\Delta_\tau^{OBS} z_{jt} | z_i\right)$ measures the probability that the dynamics at z_i follows $\Delta_\tau^{OBS} z_{jt}$; this suggests that $\Pr\left(\Delta_\tau^{OBS} z_{jt} | z_i\right)$ should decrease as function of the distance between z_i and z_{jt}^{OBS}.

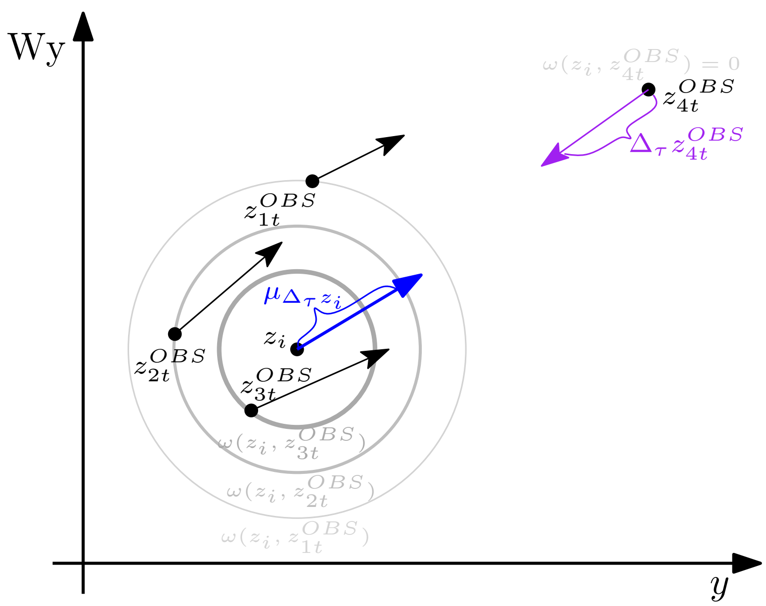


Figure 4: Local mean estimation of the *expected movement* from z_i ($\widehat{\mu}_{\Delta_\tau z_i}$) from four observed movement vectors (z_{jt}^{OBS}). Probabilities attached to each observed movement vectors, given by $\omega\left(z_i, z_{jt}^{OBS}\right)$, are a negative function of the distance between z_i and z_{jt}^{OBS}.

Following this intuition Fig. 4 depicts a point of the lattice z_i and four observed movement vectors, which origin at different distance from z_i. Function $\omega\left(z_i, z_{jt}^{OBS}\right)$ measures for each observed movement vector its probability to affect the movement at z_i; these probabilities decline with distance from z_i (i.e.

$\omega\left(z_i, z_{1t}^{OBS}\right) < \omega\left(z_i, z_{2t}^{OBS}\right) < \omega\left(z_i, z_{3t}^{OBS}\right)$), and very far observed movement vectors should have zero probability ($\omega\left(z_i, z_{4t}^{OBS}\right) = 0$). Blue vector is the *expected movement* from z_i, $\mu_{\Delta_\tau z_i}$, calculated on the base of the distribution of probabilities on the observed movement vectors.

A convenient way to calculate these probabilities is to use a kernel function to measure the distance between z_i and z_{jt}^{OBS}. In particular:

$$\omega\left(z_i, z_{jt}^{OBS}\right) = \frac{K\left(\frac{(z_i - z_{jt}^{OBS})^T S^{-1}(z_i - z_{jt}^{OBS})}{h^2}\right)\frac{\det(S)^{-\frac{1}{2}}}{2h^2}}{\sum_{t=1}^{T-\tau}\sum_{j=1}^{N} K\left(\frac{(z_i - z_{jt}^{OBS})^T S^{-1}(z_i - z_{jt}^{OBS})}{h^2}\right)\frac{\det(S)^{-\frac{1}{2}}}{2h^2}} \tag{2}$$

is assumed to be an estimate of the probability that at z_i spatial dynamics follows observed movement vectors $\Delta_\tau^{OBS} z_{jt}$, where $K(\cdot)$ is the kernel function, h is the smoothing parameter and S is the sample covariance matrix of z^{OBS}. The kernel function $K(\cdot)$ is generally a smooth positive function which peaks at 0 and decreases monotonically as the distance between the observation z_{jt} and the point of interest z_i increases (see Silverman, 1986 for technical details). The smoothing parameter h controls the width of the kernel function.[9] In the estimation we use a multivariate Epanechnikov kernel (see Silverman, 1986, pp. 76-78), i.e.:

$$K(u^T S^{-1} u) = \begin{cases} \frac{2}{\pi}(1 - u^T S^{-1} u) & \text{if } u^T S^{-1} u < 1 \\ 0 & \text{if } u^T S^{-1} u \geq 1, \end{cases} \tag{3}$$

where $u \equiv \left(z_i - z_{jt}^{OBS}\right)/h$. Multivariate Epanechnikov kernel is particularly adapted to our scope because it assigns zero probability to observed movement vectors very far from z_i.[10] The exact quantification of "very far" is provided by bandwidth h, i.e. higher bandwidth means higher number of observed movement vectors entering in the calculation of the movement at z_i.

Given Eq. (2) for each point in the lattice z_i we estimate the τ-period ahead *expected movement* $\mu_{\Delta_\tau z_i} \equiv E\left[\Delta_\tau z_i | z_i\right]$ using a *local mean estimator*, firstly proposed by Nadaraya, 1964 and Watson, 1964, where the observations are weighted by the probabilities derived from the kernel function, i.e.:[11]

$$\widehat{\mu}_{\Delta_\tau z_i} = \sum_{t=1}^{T-\tau}\sum_{j=1}^{N} \omega\left(z_i, z_{jt}^{OBS}\right)\Delta_\tau z_{jt}^{OBS} = \Pr\widehat{(\Delta_\tau z | z_i)}\Delta_\tau z^{OBS}. \tag{4}$$

The estimation of Eq. (4) strongly depends on the choice of τ. This choice is the result of a trade-off: from one hand, a too short τ can increase the noise in the estimation due to the possible presence of business-cycle fluctuations; on

[9] In all the estimation we use the optimal normal bandwidth; for a discuss on the choice of bandwidth see Silverman, 1986.

[10] Other possible kernels, as the Gaussian, does not allow such possibility.

[11] See Bowman and Azzalini, 1997 for details.

the other hand, a too long τ could contrast with the local characteristics of the estimate, increasing the probability that observed movement vectors very far from z_i affects the estimate of $\mu_{\Delta_\tau z_i}$.[12]

In the estimation we set τ=15 years.[13]

Figure (5) reports the estimated expected value of the 15-year ahead directions corresponding to a significance level of 5%.[14] The three spatial clubs present in 1991 are still there in 2008, but club C2 (the one of PIGS regions) is now well below the sample average, while club C1 (of former Eastern Bloc) moved toward 1 (i.e. sample average) along the bisector. The overall impression is that clubs C1 and C2 are converging, while the club C3 seems fairly stable as (relative) position. The core-periphery pattern observed in 2008 is therefore expected to persist over time, as describe in Figures (6) and (7) which show the geographical representational of the three clusters in 1991 and 2008. Comparing the two pictures we find that C1 is populated by the same regions on the other hand the dynamics of C2 and C3 becomes more clear.

Figure (5) points out that the assignment of a region to different spatial regimes according to the position of the region in the Moran scatter plot in the initial year can be severely biased. For example, it is common to consider regions above 1 both in term of y and $W\mathbf{y}$ as belonging to a high spatial regime, while the ones below both thresholds to a low spatial regime (see, e.g., Ertur et al., 2006). But, according our results, regions just above $y > 1$ and $W\mathbf{y} > 1$ are expected to converge to club C2 of low/medium GDP per worker and not to club C3 of high GDP per worker.

A final question is the contribution of SS versus cross-region heterogeneity to the determination of spatial clubs.[15] To answer to this question we elaborate a simple theoretical framework in the next section.

[12]For samples with a very short time span a further limit to the choice of a long τ is the relatively strong loss of observations.

[13]Therefore, our sample consists of 8 transitions for each of 254 regions.

[14]In order to formally establish the significance of the estimated directions, a bootstrap procedure is used (see Fiaschi et al., 2014) with 500 replications.

[15]Anselin, 2001 discusses how SS can derive from (possible unobservable) regions characteristics.

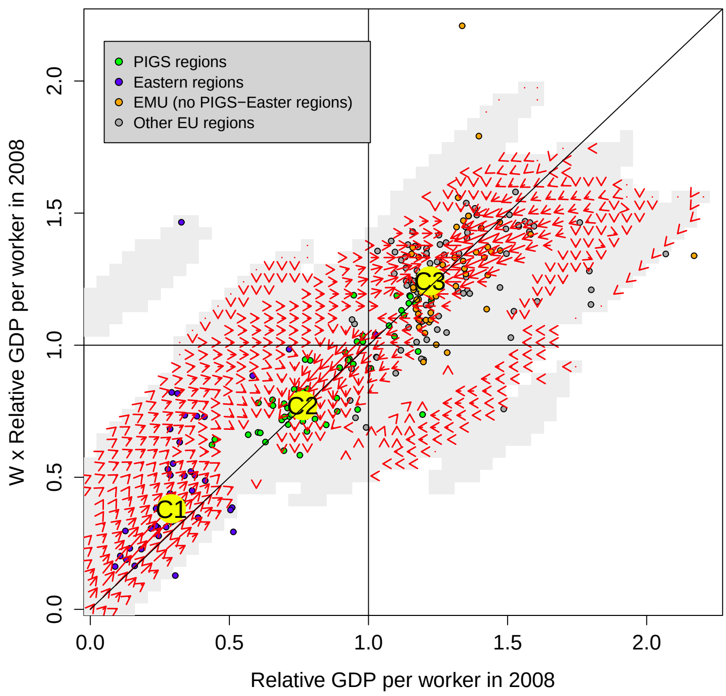


Figure 5: Moran scatter plot for 2008, the three spatial clubs, and the estimated joint dynamics for the period 1991-2008 of (relative) GDP per worker and its spatial lagged value (represented by the red arrows). The centres of three clubs of regions in 2008 are identified by *k-median* algorithm, and they are indicated by three yellow circles.

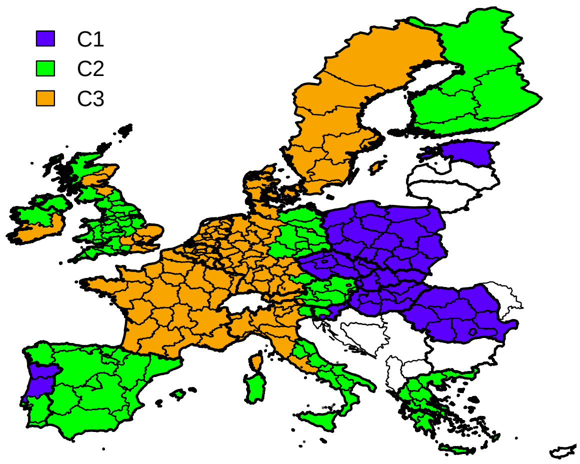


Figure 6: Map of the three spatial clubs in European regions in 1991.

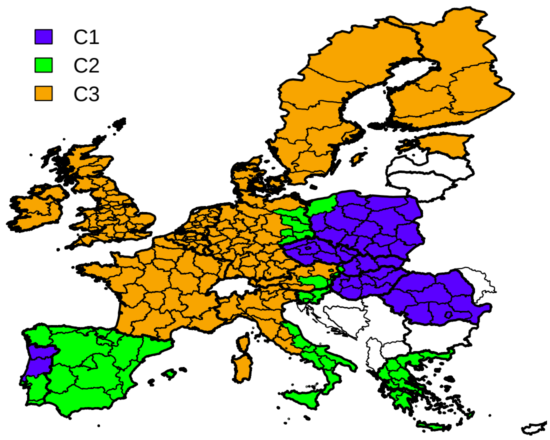


Figure 7: Map of the three spatial clubs in European regions in 2008

III. A Simple Model of Spatial Clubs

In this section we present a simple model of spatial clubs that allows to disentangle SS from the cross-region heterogeneity in individual characteristics.

III.A. The Model

Assume that total GDP of region i at period t, Y_i, is given by (see Mankiw et al., 1992):[16]

$$Y_i = \exp\left(c_i + \lambda W_i \log \mathbf{y}\right) K_i^{\alpha} H_i^{\beta} \left[L_i \exp\left(gt\right)\right]^{1-\alpha-\beta}, \qquad (5)$$

where $\exp\left(c_i + \lambda W_i \log \mathbf{y}\right)$ measures the level of technological progress (i.e. TFP) of region i as the result of an unobserved individual effect c_i, and SS $W_i \log \mathbf{y}$, where $\log \mathbf{y}$ is the vector of the log of GDP per worker normalized by technological progress $\exp\left(gt\right)$ (y is also called GDP per worker in efficient units), i.e. $y_i \equiv Y_i / \left(L_i \exp(gt)\right)$; L_i the total employment of region i; K_i the stock of physical capital; H_i the stock of human capital (HC); and, finally, g the standard exogenous and time-invariant growth rate of labour-augmenting technological progress. Parameters $\alpha, \beta \in (0,1)$ measure the elasticity of output to physical and human capital respectively, while $\lambda \in (0,1)$ the elasticity of output of region i to output of other regions. Higher λ therefore means higher technological spillovers.

[16]We omit time index if this is not source of confusion.

From Eq. (5) y_i is given by:

$$y_i = \exp\left(c_i + \lambda W_i \log \mathbf{y}\right) k_i^{\alpha} h_i^{\beta}, \tag{6}$$

where $k_i \equiv K_i / \left(L_i \exp(gt)\right)$ and $h_i \equiv H_i / \left(L_i \exp(gt)\right)$ are the physical and HC per worker in efficient units respectively.

Under the hypothesis of competitive markets, physical capital is paid to its marginal productivity, i.e.:

$$r_i = \frac{\partial y_i}{\partial k_i} = \alpha \exp\left(\frac{c_i + \lambda W_i \log \mathbf{y}}{\alpha}\right) h_i^{\frac{\beta}{\alpha}} y_i^{\frac{\alpha-1}{\alpha}}, \tag{7}$$

where r_i is the real rate of return of physical capital. If each region is assumed to be small (i.e. small-open economy hypothesis holds) with respect to world economy, and the allocation of physical capital across different regions is efficient in equilibrium, then r_i should be equal to $\bar{r}$, where $\bar{r}$ is the exogenous real rate of return prevailing at world level assumed constant over time.

Along the transition to equilibrium frictions in the capital allocation, as well as the presence of (idiosyncratic) shocks, could induce a temporary depart of r_i from $\bar{r}$. To take into account this possibility we assume that r_i follows:

$$\begin{aligned} \log r_{it} &= (1-\phi)\log r_{it-\tau} + \phi \log \bar{r} + \eta_{it}, \\ \eta_{it} &= \theta W_i^{\eta} \eta_t + \nu_{it} \end{aligned} \tag{8}$$

where $\phi \in (0,1)$ measures the frictions in the capital allocation (i.e. for $\phi = 1$ frictions are absent), τ the time-lag in the reallocation of capital (the speed of reallocation), while η_{it} is the error term which capture possible disturbances in the level of interest rate due to: a) the proximity (i.e. $\theta W_i^{\eta} \eta_t$, the spatial spillover in the error term [17]) and, b) possible idiosyncratic shocks, (i.e v_{it} the *i.i.d* shock). $\phi \in (0,1)$ ensures that r_{it} monotonically converges to $\bar{r}$.

Eqq. (7) and (8) leads to the following dynamics for the log of GDP per worker measured in efficient unit $\log y_{it}$:

$$\begin{aligned} \log y_{it} &= \left(\frac{\phi\alpha}{1-\alpha}\right)\log\alpha - \left(\frac{\phi\alpha}{1-\alpha}\right)\log\ \bar{r} + \left(\frac{\phi}{1-\alpha}\right)c_i + \left(\frac{\beta}{1-\alpha}\right)\log h_{it} + \\ &- \left[\frac{(1-\phi)\beta}{1-\alpha}\right]\log h_{it-\tau} + (1-\phi)\log y_{it-\tau} + \left(\frac{\lambda}{1-\alpha}\right)W_i \log \mathbf{y}_t + \\ &- \left[\frac{(1-\phi)\lambda}{1-\alpha}\right]W_i \log \mathbf{y}_{t-\tau} - \left(\frac{\alpha}{1-\alpha}\right)\theta W_i^{\eta}\eta_t - \left(\frac{\alpha}{1-\alpha}\right)\nu_{it}, \end{aligned} \tag{9}$$

where c_i is assumed to be constant over time.

Eq. (9) makes clear that the observed heterogeneity of GDP per worker of regions is accounted by SS (measured by λ), and by the cross-region heterogeneity in unobservable characteristics c_i.

[17] W^{η} is the *spatial matrix* in the error term, see App. A, for more details.

Finally, from Eq. (9) the equilibrium level of the (log of) GDP per worker in efficient units y^E, given by:

$$\log \mathbf{y}^E = \left[\mathbf{I} - \left(\frac{\lambda}{1-\alpha}\right)\mathbf{W}\right]^{-1}\left[\left(\frac{\alpha}{1-\alpha}\right)\log\alpha - \left(\frac{\alpha}{1-\alpha}\right)\log\bar{r} + \left(\frac{1}{1-\alpha}\right)\mathbf{c} + \left(\frac{\beta}{\alpha}\right)\log\mathbf{h^E}\right], \tag{10}$$

where $\mathbf{c}$ is the vector of unobserved time-invariant individual effects and $\mathbf{h^E}$ the vector of indexes of HC of workforce of all regions in equilibrium.

Spatial clubs in the long run can be therefore the result of a particular spatial matrix $\mathbf{W}$ (e.g. many regions are interconnected among them and others no, i.e. the exploitation of SS is spatially determined), and of a cross-regions heterogeneity with a strong spatial characterization (e.g. neighbouring regions share the same output composition and some sectors are relatively more productive than others).

IV. The Estimation of the Model

Directly inspired by Eq. (9) we estimate the following (unconstrained) model with spatial effects also in the error term:

$$\begin{aligned} \log y_{it} &= \beta_0 + \tilde{c_i} + \beta_1 \log h_{it} + \beta_2 \log h_{it-\tau} + \beta_3 \log y_{it-\tau} + \beta_4 W_i \log \mathbf{y}_t + \beta_5 W_i \log \mathbf{y}_{t-\tau} + u_{it}, \\ u_{it} &= \rho W_i \mathbf{u}_t + \epsilon_{it} \end{aligned} \tag{11}$$

where $\tilde{c_i}$ is the fixed effect (FE) of region i, β's different parameters to be estimated, and ϵ_{it} the error term.

The natural estimation method for Model (11) is a Spatial Autoregressive model with Spatial Autoregressive disturbance, i.e. SARAR model [18].

We consider as proxy of the HC the share of active population with tertiary education.[19] Moreover, we use a lag $\tau = 15$ in order to limit the possible bias in the estimate caused by serial correlation in u (i.e. endogeneity).[20].

Finally, in the estimate we do not impose any restriction on parameters deriving from Eq. (9).[21]

Table 1 shows that all estimated parameters are highly statistically significant, and with the correct sign. The estimated coefficient for HC is highly statistically significant but very low if compared to Mankiw et al., 1992's estimates of α

[18]Model (11) is estimate via maximum likelihood, with *spml* function in R.

[19]Data on tertiary education from 1995 to 2008 directly come from the Eurostat website. Backward extrapolation with non parametric regression (GAM) estimation has been used to complete the dataset for the period 1991-1994. We obtain small negative values in 1991 for two regions DK05 and FI13. Negative values are justified by the decreasing distribution in the initial years. We replace them with zero.

[20]Otherwise, if $\mathrm{Cov}(u_{it}, u_{it-1}) \neq 0$ and $\tau = 1$, then $\mathrm{Cov}(\log y_{it-1}, u_{it}) \neq 0$, i.e. endogeneity becomes a concern for the estimate.

[21]In particular, that $\beta_5 = -\beta_3 \times \beta_4$ (compare Eq. (9) with Eq. (11)).

Coefficients	Estimate	Std.Err.	t-value	Pr(> $\|z\|$)
HC				
$\log h_{it}$	0.099124	0.017587	5.6360	$1.74^{e-08***}$
Time lagged HC				
$\log h_{it-\tau}$	-0.015740	0.004259	-3.6957	0.0002193***
Time lagged GDP per worker				
$\log y_{it-\tau}$	0.025185	0.011038	2.2816	0.0225149**
Time and spatially lagged GDP per worker				
$W \log \mathbf{y}_{t-\tau}$	-0.049074	0.019134	-2.5648	0.0103244**
Spatially lagged GDP per worker				
$W \log \mathbf{y}$	0.860181	0.026078	32.9854	$< 2.2^{e-16***}$
Spatially lagged error				
Wu	-0.348068	0.122043	-2.8520	0.0043445***
Observations: 762				
AIC_c: -595639.2				

Table 1: The estimate of Model (11). Significance level: *p<0.1; **p<0.05; ***p<0.01.

and β of about 0.33 (from which an expected value of coefficient of 0.5). A possible explanation of this low coefficient is that the share of active population with tertiary education is not proportional to the stock of HC, but instead it has a strongly concave relationship. The low value of the estimated coefficient of time lagged of GDP per worker indicates that 15 years should be a sufficient time for an almost full convergence in the return on capital across regions. The estimated coefficient of the spatially lagged variable points to a presence of SS. We refer to the next section for a their more precise quantitative evaluation. Finally, the estimated coefficient for the time and spatially lagged variable is negative as expected. However, the restriction implied in the empirical Model (1) $\beta_4 = -\beta_3 \times \beta_5$ derived from Eq. (9), is not satisfied. A possible explanation can be traced to the assumption of Cobb-Douglas production function in the theoretical model of Eq.(5).

V. *Spatial Spillover versus Cross Region Heterogeneity*

One of the research questions of the paper is to disentangle the role of spatial spillover versus cross region heterogeneity on the formation of the three spatial clubs. In our analysis spatial spillovers are capture by the spatially lagged GDP per worker and its autoregressive specification while, cross region heterogeneity by the HC variable and by the FE. In particular, FE accounts for any characteristics of regions constant over time which are not directly ascribe to physical and human capital accumulation, i.e, capture the unobserved heterogeneity at regional level. Therefore, they could represent a measure of the quality of institutions or social capital generally proposed in the literature. To detect the role played by the two effects, the counterfactual distributions of the GDP per worker is presented. The counterfactual distributions in Figure 8 show what the GDP per worker distribution would be in absence of specific regional effects (FE and HC) or spatial effects (SS).

The comparison between the observed distribution in 2008 (black solid line) and the hypothetical distribution in 2008 in absence of SS in Figure 8 indicates that distributional impact of spatial spillover SS is very important both in terms of dispersion (10 points in terms of Gini index) and polarization (no polarization in the counterfactual distribution) (compare blue with black lines is Figure 8). In particular, the Gini index decreases to 0.13, and the distribution becomes unimodal and more concentrate around zero. Different conclusion holds looking at the counterfactual distribution with no HC, where their contribution to explain the distribution of GDP per worker is negligible both on dispersion and polarization. On the contrary, the estimated fixed effects FE explain a significant share of total dispersion (4 points basis out of 23 of Gini index), and a large share of polarization (BIPOL with no FE is equal to 0.46 versus 0.78 of the actual distribution, see Figure 8).

	Observed 2008	No SS 2008	No FE 2008	No HC 2008
Gini	0.23	0.13	0.19	0.22
BIPOL	0.78	NA	0.46	0.8

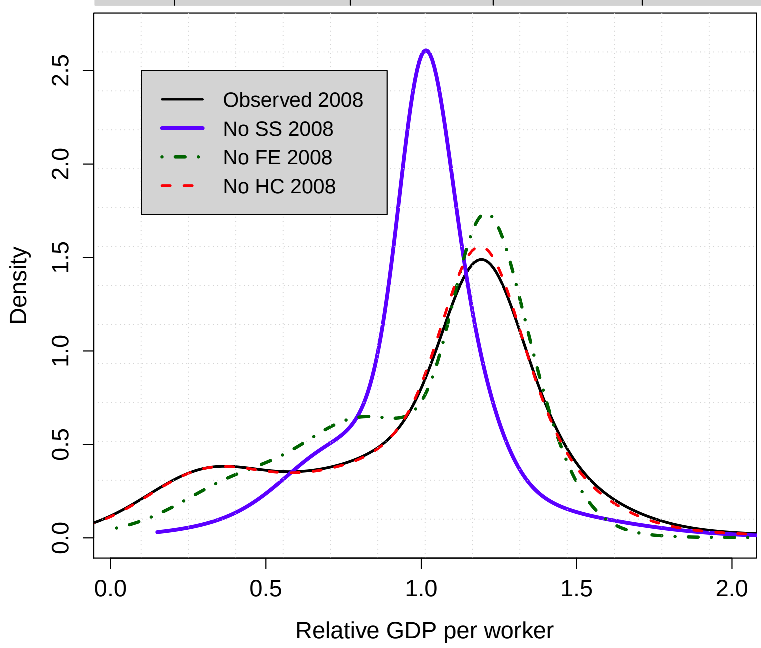


Figure 8: Observed versus counterfactual distributions of GDP per worker in 2008 with no SS (spatial spillovers), no FE (fixed effects) and no heterogeneity in HC (human capital).

Figures 9 and 10 show the distribution of FE and GDP per worker in 2008 at regional level. FE map has e geographical patter very similar to GDP per worker.

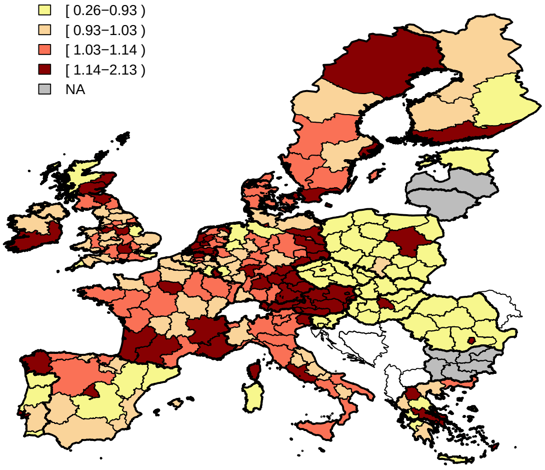


Figure 9: Spatial distribution of the estimated fixed effects.

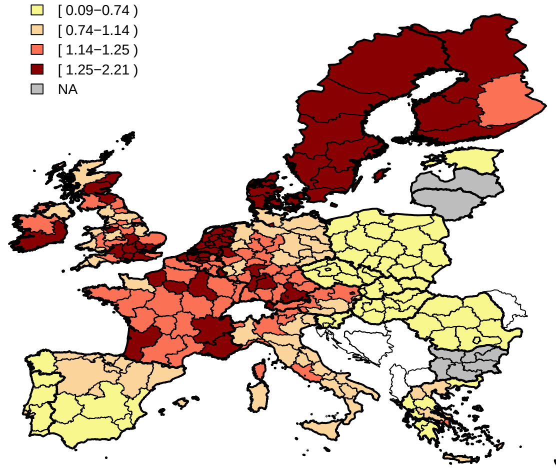


Figure 10: Spatial distribution of GDP per worker in 2008.

	Moran's I	p-value
GDP per worker in 1991	0.767^{***}	$< 2.2e-16$
GDP per worker in 2008	0.764^{***}	$< 2.2e-16$
FE	-0.005	0.517

Table 2: Moran's I statistic for three different series: GDP per worker in 1991, 2008 and FE.

The correlation between the estimated fixed effects and GDP per worker in 2008 is about 0.55 but some differences emerge among which the most important is the less pronounced core-periphery pattern of FE (compare Figures 9 and 10). This intuition is confirmed by the Moran's statistic.

Table 2 reports the values of the Moran's I statistic for GDP per worker in 1991, 2008 and FE. In particular, Moran's I calculated on FE becomes no significant reflecting the absence of spatial dependence, while the Moran's I calculated on the series of per worker GDP in the 2008 is positive, statistically significant and no different from those in 1991 as expected.

Finally, to complete the analysis, the scatter plot and the non parametric estimation between FE and relative GDP per worker in 2008 is presented in Figure 11. Figure 11 gives a clear representation of the analysis, confirming the higher and positive impact of FE to explain the distribution of GDP per worker in the last year, and consequently on the formation of spatial clubs [22].

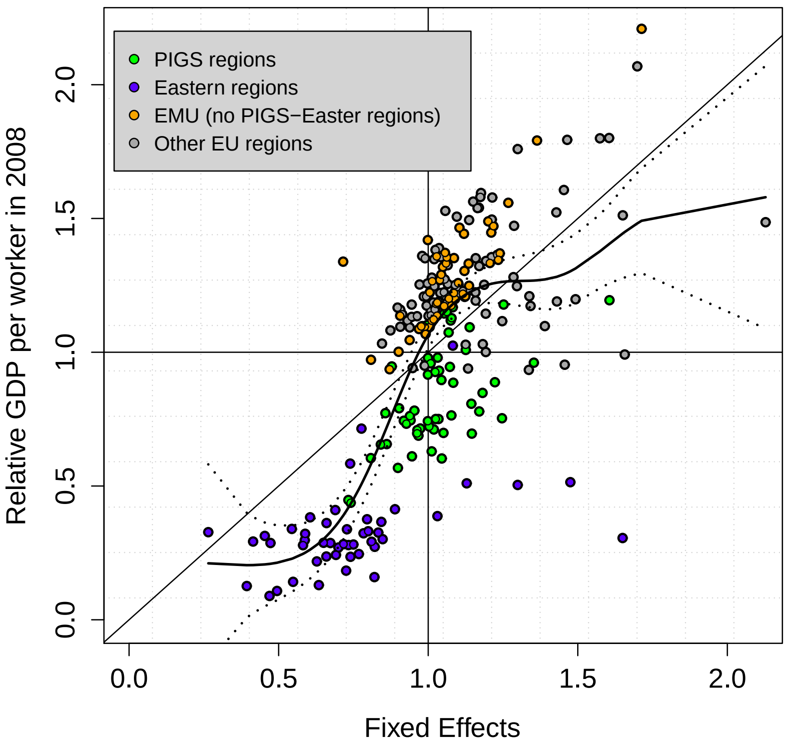


Figure 11: Scatter plot of fixed effects versus relative GDP per worker in 2008. Solid line is the nonparametric estimation while dotted lines are the confidence bands at 95%.

VI. Concluding Remarks

We identify spatial clubs in European regions by a new methodology which can circumvent the drawback of the standard approach based on simple Moran scatter plot (see, e.g., Ertur et al., 2006). By the estimate of a simple model we conclude that spatial spillovers are present across European regions, and their contribution to the emergence of spatial clubs is high as well as the individual

[22] The non parametric specification is expressed as:

$$GDPpw_{i2008} = f(FE_i) + \varsigma_i, \tag{12}$$

where $GDPpw_{i2008}$ is the level of the GDP per worker in 2008, FE the fixed effects estimated from Model 11, and ς_i is the error component. The estimated model could explain about 60% of the total variance, as showed by the $\bar{R}^2 = 0.61$.

regional (unobserved) characteristics. Heterogeneity in human capital seems to play a marginal role for the distribution of GDP per worker.

Acknowledgements A previous version of this paper was presented at 13rd International Workshop Spatial Econometrics and Statistics in Toulon, April 2014; 27^{th} ERSA Summer School in Spatial Econometrics and Regional Analysis, Adam Mickiewicz University in Poznan, Poland, July 2014; RCEF-2014 in Rimini, June 2014; Associazione Italiana di Scienze Regionali (AISRe) XXXV, September 2014; 54rd European Regional Science Association ERSA Congress in St Petersburg, August 2014; 7th Jean Paelinck Seminar of Spatial Econometric, November 2014 at the University of Zaragoza, Spain. We are very grateful to Stefano Magrini, Giovanni Millo, Michele Battisti, Thomas Bassetti, Coricelli Fabrizio and the participants to those meetings their helpful comments. Usual disclaimer applies.

Affiliation and Address of the Authors

Davide Fiaschi: Dipartimento di Economia e Management, University of Pisa, Pisa, Italy.

Lisa Gianmoena: Institute of Advanced Studies (IMT), Lucca, Italy.

Angela Parenti:Institute of Advanced Studies (IMT), Lucca, Italy.

References

Anderson, G., O. Linton, and T. Leo (2012, March). A polarization-cohesion perspective on cross-country convergence. *Journal of Economic Growth 17*(1), 49–69.

Anselin, L. (2001). Spatial econometrics. In B. Baltagi (Ed.), *A Companion to Theoretical Econometrics*, pp. 310–330. Oxford: Blackwell.

Bowman, A. and A. Azzalini (1997). *Applied Smoothing Techniques for Data Analysis: the Kernel Approach with S-Plus Illustrations.* Oxford: Oxford University Press.

Ertur, C., J. Le Gallo, and C. Baumont (2006). The european regional convergence process, 1980-1995: Do spatial regimes and spatial dependence matter? *International Regional Science Review 29*(1), 3–34.

Fiaschi, D., L. Gianmoena, and A. Parenti (2014). Local directional moran scatter plot. *Mimeo*.

Fiaschi, D. and M. Romanelli (2009, October). Nonlinear dynamics in welfare and the evolution of world inequality. Temi di discussione (Economic working papers) 724, Bank of Italy, Economic Research and International Relations Area.

Fujita, M., P. Krugman, and A. J. Venables (1999). *The Spatial Economy.* Cambridge: MIT Press.

Leisch, F. (2006). A toolbox for k-centroids cluster analysis. *Computational Statistics and Data Analysis 51*(2), 526–544.

Mankiw, N., D. Romer, and D. Weil (1992). A contribution to the empirics of economic growth. *Quarterly Journal of Economics 107*, 407–437.

Nadaraya, E. (1964). On estimating regression. *Theory of Probability & Its Applications 9*(1), 141–142.

Silverman, B. (1986). *Density Estimation for Statistics and Data Analysis.* London: Chapman and Hall.

Watson, G. (1964). Smooth regression analysis. *Sankhyā: The Indian Journal of Statistics, Series A*, 359–372.

A Spatial Weight Matrices

The Spatial Matrix W in the dependent variable y

The *spatial matrix* W is a $(N \times N)$ matrix with zeros on its main diagonal. The off-diagonal elements, w_{ij} reflect the spatial dependence i.e. the spatial spillover SS of unit j on unit i.

In the rest of paper we consider a row-standardized W based on the centroid distances between each pair of spatial units i and j, denoted by d_{ij}. In particular, the spatial matrix W in the dependent variable y is defined in term of the inverse of the square of the great circle distance between centroids of regions (i.e. $1/d_{ij}^2$) with a distance cut-off equal to the first quartile (Q1=403 miles).

The element w_{ij} of $\mathbf{W}$ is therefore given by:

$$
\begin{aligned}
w_{ij} &= \frac{w_{ij}^*}{\sum_j w_{ij}^*} \\
w_{ij}^* &= \begin{cases} d_{ij}^{-2} & \text{if } i \neq j \text{ and } d_{ij} \leq d_{Q1}; \\ 0 & \text{otherwise.} \end{cases}
\end{aligned}
$$

The Spatial Matrix W^η in the error term u

In the same way W^η is a $(N \times N)$ matrix which describe the spatial dependence in the error term. W^η is define in term of the inverse of the square of the great circle distance between centroids of regions with a distance cut-off equal to the second quartile (Q2=671 miles), which imply a relatively more sparse *spatial matrix* respect to W. The different specification of W^η allows us to take into account the dynamics of the process specified in Eq. (**??**), i.e the changes in y_i and $W_i\mathbf{y}$ after $\tau = 15$ periods.

The element w_{ij}^η of $\mathbf{W}^\eta$ is therefore given by:

$$
\begin{aligned}
w_{ij}^\eta &= \frac{w_{ij}^{\eta *}}{\sum_j w_{ij}^{\eta *}} \\
w_{ij}^{\eta *} &= \begin{cases} d_{ij}^{-2} & \text{if } i \neq j \text{ and } d_{ij} \leq d_{Q2}; \\ 0 & \text{otherwise.} \end{cases}
\end{aligned}
$$

B Descriptive Statisitcs

Table 3: Descriptive Statistics

	$y_{it} = GDPpwRel$	$y_{it-\tau} = GDPpwRel.lag$	$Wy_{it} = W.GDPpwRel$	$Wy_{it-\tau} = W.GDPpwRel.lag$	$h_{it} = HC$	$h_{it-\tau} = HC.lag$
min	-2.48	-2.81	-2.16	-2.78	2.75	0.00
max	0.80	0.67	0.77	0.57	4.13	4.53
mean	-0.13	-0.19	-0.11	-0.16	3.55	3.17
var	0.37	0.56	0.28	0.44	0.06	0.22
std.dev	0.61	0.75	0.53	0.66	0.24	0.47

Table 4: Correlation Matrix

	$y_{it} = GDPpwRel$	$y_{it-\tau} = GDPpwRel.lag$	$Wy_{it} = W.GDPpwRel$	$Wy_{it-\tau} = W.GDPpwRel.lag$	$h_{it} = HC$	$h_{it-\tau} = HC.lag$
GDPpwRel	1.00	0.97	0.91	0.92	0.66	0.36
GDPpwRel.lag	0.97	1.00	0.91	0.93	0.59	0.31
W.GDPpwRel	0.91	0.91	1.00	0.98	0.58	0.35
W.GDPpwRel.lag	0.92	0.93	0.98	1.00	0.55	0.33
HC	0.66	0.59	0.58	0.55	1.00	0.60
HC.lag	0.36	0.31	0.35	0.33	0.60	1.00

C Region List

Austria	DE24	ES11	FR61	NL13	PL43	UKD1
AT11	DE25	ES12	FR62	NL21	PL51	UKD2
AT12	DE26	ES13	FR63	NL22	PL52	UKD3
AT13	DE27	ES21	FR71	NL23	PL61	UKD4
AT21	DE3	ES22	FR72	NL31	PL62	UKD5
AT22	DE41	ES23	FR81	NL32	PL63	UKE1
AT31	DE42	ES24	FR82	NL33	Portugal	UKE2
AT32	DE5	ES3	FR83	NL34	PT11	UKE3
AT33	DE6	ES41	Greece	ITC3	PT15	UKE4
AT34	DE71	ES42	GR11	ITC4	PT16	UKF1
Belgium	DE72	ES43	GR12	ITD1	PT17	UKF2
BE1	DE73	ES51	GR13	ITD2	PT18	UKD4
BE21	DE8	ES52	GR14	ITD3	Romania	UKD5
BE22	DE91	ES53	GR21	ITD4	RO11	UKE1
BE23	DE92	ES61	GR22	ITD5	RO12	UKE2
BE24	DE93	ES62	GR23	ITE1	RO21	UKE3
BE25	DE94	ES63	GR24	ITE2	RO22	UKE4
BE31	DEA1	ES64	GR25	ITE3	RO31	UKF1
BE32	DEA2	ES7	GR3	ITE4	RO32	UKF2
BE33	DEA3	Finland	GR41	ITF1	RO41	UKF3
BE34	DEA4	FI13	GR42	ITF2	RO42	UKG1
BE35	DEA5	FI18	GR43	ITF3	Slovenia	UKG2
Cypro	DEB1	FI19	Hungary	ITF4	SE11	UKG3
Czech Rep.	DEB2	FI1A	HU1	ITF5	SE12	UKH1
CZ01	DEB3	FI2	HU21	ITF6	SE21	UKH2
CZ02	DEC	France	HU22	ITG1	SE22	UKH3
CZ03	DED1	FR1	HU23	ITG2	SE23	UKI1
CZ04	DED2	FR21	HU31	NL41	SE31	UKI2
CZ05	DED3	FR22	HU32	NL42	SE32	UKJ1
CZ06	DEE	FR23	HU33	Poland	SE33	UKJ2
CZ07	DEF	FR24	Ireland	PL11	Slovakia	UKJ3
CZ08	DEG	FR25	IE01	PL12	SI01	UKJ4
Germany	Denemark	FR26	IE02	PL21	SI02	UKK1
DE11	DK01	FR3	Italy	PL22	SK01	UKK2
DE12	DK02	FR41	ITC1	PL31	SK02	UKK3
DE13	DK03	FR42	Luxemburg	PL32	SK03	UKK4
DE14	DK04	FR43		PL33	SK04	UKL1
DE21	DK05	FR51	Netherlands	PL34	United Kingdom	UKL2
DE22	Estonia	FR52	NL11	PL41	UKC1	UKM2
DE23	Spain	FR53	NL12	PL42	UKC2	UKM3

Table 5: List of EU regions in the sample.

Discussion Papers
Collana del Dipartimento di Economia e Management, Università di Pisa (ISSN: 2039-1854)