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The convergence process of the European regions: the role of Regional Policy and the Common Agricultural Policy

The study investigates the convergence of labour productivity in 204 NUTS2 regions of the EU-15 between 1995 and 2006. The main objective of our work was to assess whether and to what extent European Union (EU) policies (Regional Policy and the Common Agricultural Policy) have been effective in promoting economic growth and fostering the process of convergence of EU regions. These policies can have an asymmetric spatial impact, even if some concrete steps have been taken to avoid an excessive concentration of costs or benefits. To verify the effects of EU policies we compare different scenarios: with/without EU policies. Under a methodological profile, we adopt the Solovian model proposed by Mankiw *et al.* (1992). For the estimates we used an econometric approach based on spatial filters with characteristics similar to *Geographically Weighted Regression* (GWR) in order to obtain consistent estimates of both the convergence parameters β and the impact of the conditioning variables, policy measures in particular. Our technique allows the estimation of different convergence rates for each region and management of both the presence of spatial spillovers and structural differences in the regional economies. The results indicate that global convergence rates are comparable to those obtained in some other studies, while local coefficients help to interpret the regional growth paths in a more realistic way. Finally, we utilise a quasi-experimental design, the Regression Discontinuity, for comparing the results of policy interventions, in terms of regional β-convergence rates, with a 'counterfactual' scenario.

Keywords: Regional growth, Structural Funds, CAP subsidies, productivity convergence, spatial filters.

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Introduction

Currently a large share of the European Union (EU) budget is directed toward two policies with different implications at territorial level. The financial resources of the Cohesion Policy (CP)[1] represent about one third of the total EU budget while the Common Agricultural Policy (CAP) accounts for over 40%. The main operational tools of Cohesion Policy are the Structural Funds (SF) whose aim is reducing regional disparities in terms of income, wealth and opportunities. On the other hand, the CAP has a more sectoral focus and is configured with an only partial spatial dimension (EC, 2010), despite the fact that since 1992 it increased its effects on the cohesion process. This means that the territorial impacts of these policies could be asymmetric, not allowing overcoming of territorial disparities.

In considering the distribution of CAP subsidies we should take into account that 'growth in poorer regions is greatly hampered by an unfavourable industrial structure (dominated by agriculture)' (Cappelen *et al.*, 2003, p.640) and that according to Montresor and Pecci (2008) in some regions CAP subsidies were far higher than those of the CP and focused mainly in the more developed regions. Loosely speaking the issue consists of choosing if the distribution CAP subsidies must follow criteria based on efficiency or on equity.

Starting from these previous findings, the main objective of this study is to answer this question: how effective has the EU regional development policy supported by the SF and the CAP been in promoting economic growth and in fostering the convergence of EU regions?

It should be recalled that in 1989, when the EU CP began, there were strong doubts about its effectiveness. These low expectations were mainly related to the poor performances of regional development policies carried out in the Member States (MS) and to the fear that the less developed areas would not be able to sustain the competition levels of the core areas of the EU (Rumford, 2000; Leonardi, 2006).

In spite of these initial hesitancies, it is objective that 'a strong overall regional convergence has taken place in the EU in the last 25 years, in the EU-15 only until the end of the 1990s, with a change of trend since then, in the EU-27 between 2001 and 2005. In the current decade employment rates have been slowly converging in both areas, while productivity of labour has converged only in the EU-12 area' (Barca, 2009, p.105).

It is still difficult to sustain that economic growth was induced from CP rather than from other factors, considering that the effects of CP were not uniform among regions with similar economic conditions. In any case, CP helped to change the nature of European integration: from an integration based mainly on the creation of the single market, it allowed integration based on mutual solidarity. Another important contribution is linked to the rediscovery of the territorial dimension rather than sectoral one. Nevertheless in the Fourth Report on Economic and Social Cohesion (EC, 2007), the European Commission (EC) points out (p.x) that 'In spite of this [economic] progress [of less developed regions], absolute disparities remain large. This is partly as a result of recent enlargement and partly as growth tends to concentrate – during the initial phases of development – in the most dynamic areas within countries'. These doubts about the effectiveness of CP are also reported by Barca (2009) when emphasising the necessity to modify the CP.

In our work we adopt the β-convergence model proposed by Barro and Sala-i-Martin (1992) and by Mankiw *et al.* (1992) for evaluating the effects of SF and CAP subsidies on the convergence of labour productivity in 204 NUTS2 EU-15 regions[2], between 1995 and 2006[3]. This model sug-

[1] Cohesion Policy in the study stands for Regional Policy.

[2] The regions in the sample are shown in Appendix.

[3] In the database of the European Farm Accountancy Data Network (FADN) the information on subsidies at regional level is incomplete before 1995. This is the reason why the beginning of the analysed period does not coincide with 1994, the starting year of the second operational period of SF.

gests that the regions with lower values of productivity grow faster than those with higher values (less developed regions would catch up with more advanced regions): this implies a negative correlation between growth rates of productivity and the initial levels of this variable. This model has some limitations related to its inability to manage both structural heterogeneity of the economies (Durlauf *et al.*, 2005) and the spatial dependence (Baumont et al., 2003), that can be overcome using a methodology based on spatial filters (Griffith, 2008).

To exceed the limited capacity of this cross-country regression model to take into account structural heterogeneity, we use a model that can be considered a generalisation of the model proposed by Solow (1956) in which each country/region follows this model, but their aggregate production functions are free to change (Brock and Durlauf, 2001). As a consequence, the steady states are free to vary across regions without imposing a preliminary hypothesis about the type of convergence (absolute, conditional or clubs).

The inclusion of spatial filters, derived from a spatial weights matrix, is able to manage both spatial correlation in residuals and spatial interaction among variables and then the spatial spillovers effects (Griffith, 2003). In addition, this spatial econometric tool allows estimating regional parameters that are decomposable into a global trend effect and a local one. In this way we obtain a double indication: the general impact of the variables (shown by their coefficients like in classic ordinary least square – OLS – output) and a regionally targeted effect (a local and univocal coefficient). This represents a decisive step forward for understanding and assessing the specific effects of public policies on growth and socio-economic dynamics.

For evaluating the effects of CP on the convergence process of European regions, we utilise a quasi-experimental design, the Regression Discontinuity (RD), to compare the results of policy interventions, in terms of regional β-convergence rates (the output of the spatial filtering model), with a 'counterfactual' scenario to estimate what would have happened in the absence of such interventions.

In order to give a better contextualisation of our results, we highlight some significant outcomes of previous studies on convergence of European regions. A first set does not consider the spatial dimension of the regional economies. Among these, Cuadrado-Roura (2001) tested the hypothesis that regions with an initial level of GDP per capita below the EU average had an above-average growth rate in the period 1977-1994. The estimated convergence rate was less than 2%. López-Bazo (2003) reached similar results examining the period 1975-1996. Among the authors whose aim is to verify the conditional convergence, Fagerberg and Verspagen (1996), Cappelen *et al.* (2003) and Geppert *et al.* (2005) detected a low or absence of the convergence process, while Neven and Gouyette (1995), considering two different regimes for northern and southern EU regions, found a significant convergence rate. Basile *et al.* (2001) identified a significant convergence process; finally Martin (2001) distinguished various groups of regions among Objective 1 regions, in different sub-periods.

The most recent contributions take into account the spatial dimension (Baumont *et al.*, 2003; Fischer and Stirböck, 2005; Dall'Erba and Le Gallo, 2006; Arbia *et al.*, 2010). The inclusion of spatial effects causes a reduction of the estimated speed of the global convergence process to be reduced, but it highlights that the speed of convergence is higher in the EU's poorest regions.

Some authors adopted the β-convergence model to analyse the effect of CP on convergence. Cappelen *et al.* (2003) found that the 1988 reform of SF increased its effectiveness in the poorest regions. Rodríguez-Pose and Fratesi (2004) examined how SF support was allocated among different development axes in Objective 1 regions for the period 1989-1999. They found no significant impact of SF on infrastructures or business support, while investment in human capital had medium-term positive effects and support for agriculture had short-term positive effects on growth.

Ederveen *et al.* (2006) attempted to assess the efficacy of SF following the approach proposed by Burnside and Dollar (2000). Their findings pointed to the absence of a globally significant impact of SF on regional growth but the support allocated in the regions with high quality of institutions was effective, leading to the conclusion that SF are conditionally effective. Dall'Erba and Le Gallo (2007) included the spatial effects in the estimation of a conditional β-convergence model, analysing separately each of the five SF objectives. The results indicate that their impact was insignificant, very small and even, in some cases, negative. In particular, support under Objective 1 was found to have a positive impact in the core regions but an insignificant one in the peripheral regions.

Among the few authors who considered the impact of CAP subsidies in the estimation of the convergence process of EU regions, we recall Esposti (2007) who assessed the consistency of CAP measures with Objective 1 funds for the period 1989-2000. This study found a positive impact of Objective 1 funds on the convergence process of 206 EU Regions and that CAP expenditure did not have a counter-treatment effect, although its positive impact on growth was in fact negligible.

The economic and social cohesion in the EU has become even more important since the accession of Spain and Portugal in 1986 and the adoption of the programme to complete the internal market in 1992. The necessary financial resources for achieving the objectives were obtained through the SF reform. This reform, completed at the end of 1988, identified five objectives to assist the least-favoured regions and to reduce disparities in development in comparison with the most advanced regions.

Objective 1 consisted in promoting the development and structural adjustment of the regions whose development was lagging behind; Objective 2 aimed to convert declining industrial regions; The goals of Objective 3 were combating long-term unemployment; the target of Objective 4 was facilitating the occupational integration of young people; that of Objective 5a was speeding up the adjustment of agricultural structures, while with Objective 5b the intent was promoting the development of rural areas. Objective 1 and other Objectives were mutually exclusive. SF were allocated within operational periods: the first running from 1989 to 1993, the second from 1994 to 1999, the third from 2000 to 2006 and the fourth from 2007 to 2013. During the second

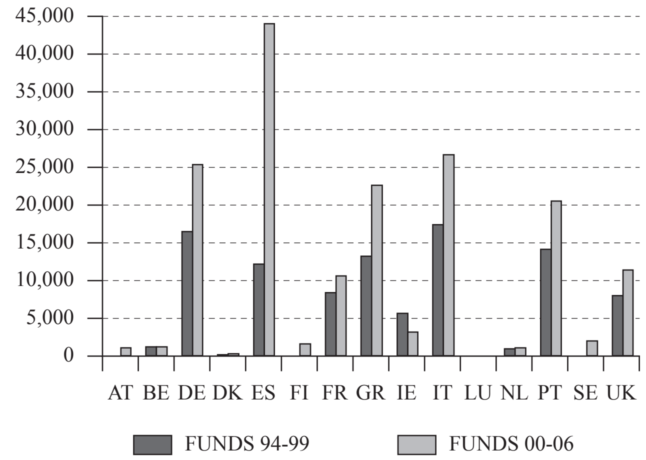

Figure 1: Amount of Structural Funds (Objectives 1, 2, 5b) per EU Member State (MECU).

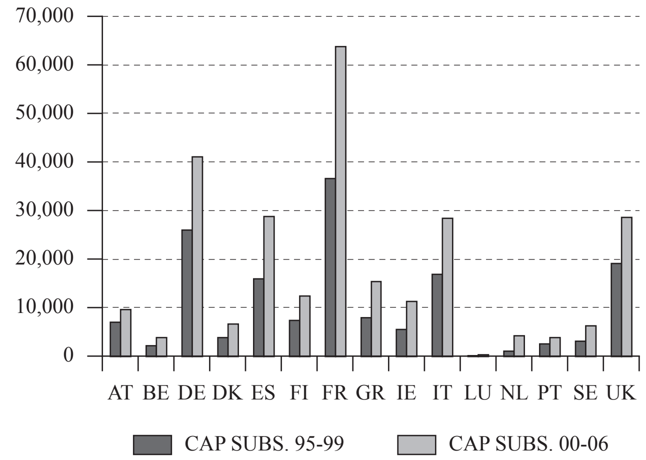

Figure 2: Amount of Common Agricultural Policy funding per EU Member State (MECU).

period the Objective 6 (sparsely populated area) was added. The Agenda 2000 agreement reduced the objectives from six to three. Objective 1 was unchanged, while the new Objective 2 brought together the former Objectives 2 and 5b. In our work we consider only the regionally targeted Objectives: 1, 2 and 5b for the second period and Objectives 1 and 2 for the third period[4].

The absolute value of the resources in millions of Euro (MECU) for each country in the two considered programming periods are shown in Figure 1. Naturally the SF increased significantly in MS with Objective 1 regions: Germany, Greece, Italy, Portugal and Spain, but, excluding for Objective 1, they represented a very small percentage of GVA.

The total CAP subsidies considered in the study[5] are shown in Figure 2. The MS that received the largest shares of subsidies, in absolute terms, were in order: France, Germany, UK and Italy. Generally the amounts of CAP subsidies were 50% bigger than SF. Therefore, at least for the amount of devoted resources, the role of CAP support cannot be considered separately from CP support in evaluating regional development.

The paper is organised as follows: in the next section we describe the empirical and spatial models, and in the following one the estimation result. In the final section we discuss the application of the Discontinuity Regression.

The empirical and spatial model

In our work we estimate the convergence process on labour productivity by the well-known cross-sectional β-convergence model defined as follows (Durlauf *et al.*, 2005):

$$\frac{(\ln y_{it} - \ln y_{i0})}{t} = \alpha + \beta \ln y_{i0} + Z\varphi + \varepsilon \quad (1)$$

where α represents the constant term, i is the region index, y_{i0} is the initial productivity level (*GVA_EMP95*) (the variables are described in Table 1), y_{it} is the final productivity level (*GVA_EMP06*), and Z is a matrix of explanatory variables. β is the so called convergence coefficient, φ is the vector of the parameters and ε the i.i.d. error term[6].

Table 1: The variables entered in the models.

Variable	Description
GVA_EMP06_i	logarithm of local rate of GVA per worker in 2006
GVA_EMP95_i	logarithm of local rate of GVA per worker in 1995
$DISC\_GVA_i$	logarithm of local rate of employment growth (mean between 1995 and 2006) + 0.03
INV_GVA_i	logarithm of local rate of investment on GVA (mean between 1995 and 2006) as proxy of saving rate
EMP_AGRI_i	logarithm of local rate of employment on agriculture on total employment (mean between 1995 and 2006)
EMP_SERV_i	logarithm of local rate of employment on services on total employment (mean between 1995 and 2006)
LL_LEAR_i	logarithm of workers participating in lifelong learning programmes on total workers (mean between 1995 and 2006)
$OB1\_GVA_i$	logarithm of yearly average local level of Objective 1 Fund for the whole period divided by the level of GVA at the beginning of the period
$OB2\text{-}5\_GVA_i$	logarithm of yearly average local level of Objective 2 Fund for the whole period plus Objective 5b Fund for period 1994-1999 divided by the level of GVA at the beginning of the period
$SUBS\_GVA_i$	logarithm of yearly average local level of CAP subsidies for the whole period divided by the level of GVA at the beginning of the period

The parameter β is expected to be negative and approximates the speed of convergence towards the steady state: less productive regions should grow faster than more productive. The inclusion of the set of control variables (Z) in the model (1) tests the conditional β-convergence hypothesis, which takes place if each region reaches its own steady state, converging in the long run to different levels of per worker

[4] The SF for Objective 2 and 5b, when assigned at national level, were reassigned to eligible regions on the base of their population.

[5] In our study we consider the value of total subsidies, extracted from Standard Result database, that are contained in the variable SE605 of the European FADN. In particular the variable SE 605 covers total subsidies – European and national, I and II pillar of the CAP, coupled and decoupled – excluding subsidies on investments.

[6] The data about GVA, employment and investment are taken from Cambridge Econometrics' database, while data about lifelong learning participants from Eurostat Regio. Data on Funds allocation are taken from EC (1995a, 1995b, 1999 and 2006).

output. As in Mankiw *et al.* (1992), we included in *Z* the physical capital investment rates (*INV_GVA*) and the term *DISC_GVA* to take into account the variable ($n+g+\delta$), where n is the employment growth, g the technological progress, and δ the depreciation rate. As suggested by Mankiw *et al.* (1992) we fixed $g+\delta$ equal to 0.03 while we estimated n.

In our cross-section growth models (with and without SF and CAP subsidies), in addition to mentioned variables, we added some control variables related to the s*ocial filter* (Crescenzi *et al.*, 2007) able to catch the structures of the regional economies. These variables are somehow connected to the SF and CAP subsidies, as they depict the 'state of the economy' where the policy instruments are implemented. We considered the share of services employment (*SERV_EMP*) and agricultural employment (*AGRI_EMP*) to capture respectively the sector with higher and lower productivity. We also included the participants of lifelong learning programmes (*LL_LEAR*) for representing both the degree of accumulation of knowledge and the human capital investment rate.

We estimated two models (where the parameters are free to vary locally) specified as follows:

1 - Base model:

$$(GVA\_EMP06_i - GVA\_EMP95_i)/12 =$$
$$\alpha + \beta GVA\_EMP95_i + \varphi_1 DISC\_GVA_i + \varphi_2 INV\_GVA_i +$$
$$\varphi_3 EMP\_AGRI_i + \varphi_4 EMP\_SERV_i + \varphi_5 LL\_LEAR_i + \varepsilon_i$$

2 - Base model + SF + CAP subsidies:

$$(GVA\_EMP06_i - GVA\_EMP95_i)/12 =$$
$$\alpha + \beta GVA\_EMP95_i + \varphi_1 DISC\_GVA_i + \varphi_2 INV\_GVA_i +$$
$$\varphi_3 EMP\_AGRI_i + \varphi_4 EMP\_SERV_i + \varphi_5 LL\_LEAR_i + \varepsilon_i +$$
$$\varphi_6 OB1\_GVA_i + \varphi_7 OB2\text{-}5\_GVA_i + \varphi_8 SUBS\_GVA_i + \varepsilon_i$$

For implementing the spatial filtering model stated above we need to specify a spatial weights matrix able to take into account the institutional, socio-economic and spatial relations among regions. This kind of matrix is a way to model the externalities as conceived by Krugman (1991). Our spatial weights matrix is based on a *Gravity Model Indices* (Keeble *et al*., 1981, 1988) because using this indicator we are able to take into account both the distance and potential attraction among regions. The influence (relative economic potential) of a certain region on another, in fact, is directly proportional to the product of the economic activity (or 'mass') of the two regions, and inversely proportional to the distance *dist* (measured in kilometres) separating them. In the obtained square matrix every row shows the 'relative economic potentials' of a determined region with respect to the others. The 'total economic potential' of each location is found by summing by row all the 'relative economic potentials'. In the study, the mass *m* for each region is assumed to be equal to the log of employment productivity in 1995, which is the main variable of the used cross-sectional growth model[7].

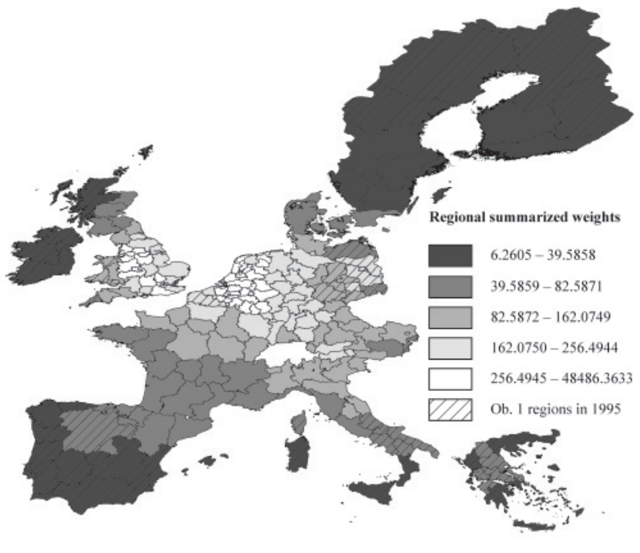

Figure 3: Economic potential of the location according to Gravity Model Indices used in our model (EU NUTS2 regions).

The spatial weights matrix for *n* regions, with zero on the principal diagonal, is defined as:

$$SW = \begin{pmatrix} 0 & \dfrac{m_1 \times m_2}{(dist_{1,2})^2} & \cdots & \dfrac{m_1 \times m_n}{(dist_{1,n})^2} \\ \dfrac{m_2 \times m_1}{(dist_{2,1})^2} & 0 & \cdots & \dfrac{m_2 \times m_n}{(dist_{2,n})^2} \\ \vdots & \vdots & \ddots & \vdots \\ \dfrac{m_n \times m_1}{(dist_{n,1})^2} & \dfrac{m_n \times m_2}{(dist_{n,2})^2} & \cdots & 0 \end{pmatrix} \begin{matrix} = \sum_{i=1}^{n} \dfrac{m_1 \times m_i}{(dist_{1,i})^2} \\ = \sum_{i=1}^{n} \dfrac{m_2 \times m_i}{(dist_{2,i})^2} \\ \vdots \\ = \sum_{i=1}^{n} \dfrac{m_n \times m_i}{(dist_{n,i})^2} \end{matrix} \qquad (2)$$

The map of the regional economic potential in Figure 3 is quite similar to that of Copus (1997).

The *SW* matrix is standardized using a W coding-scheme (Tiefelsdorf *et al*., 1999) that keeps the 'relative economic potential' of every region with respect to the others standardizing them by row. Testing the presence of spatial autocorrelation among variables using Moran's test we can exclude the classical assumption of independence of observations for each variable (Tiefelsdorf and Griffith, 2007), justifying the choice of using spatial filtering technique, through which we can restore the assumption of independence of observations for each variable. While Getis' spatial filters (1995) separately filter each variable splitting its spatial component from the non-spatial one, our spatial filters model is based exclusively on the spatial weights matrix and on its Moran Coefficient (*MC*) defined as:

$$MC = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(y_i - \overline{y_i})(y_j - \overline{y_j})}{\sum_{i=1}^{n}(y_i - \overline{y_i})^2} = \qquad (3)$$
$$\frac{n}{1'W1} \frac{Y'M(SW)MY}{Y'MY}$$

where i and j refer to different spatial units (i.e. cell centroids) of which there are n, and y is the data value in each. The right side of equation (3) represents the matricial form of *MC* where $M = \left(I - \dfrac{11^t}{n}\right)$ is the matrix in which I is the

[7] Keeble et al. (1981, 1988) chose GDP or GDP in PPS like mass variable. In our case, we chose the log GVA per worker in 1995 like mass because it is the main variable of the growth model.

identity matrix of size n-by-n, 1 is a vector of one dimension n-by-1 and the superscript t points the transposed matrix. The peculiarity of the M matrix is that it centres the vector of data value Y.

Tiefelsdorf and Boots (1995) demonstrate that each of the n eigenvalues of expression

$$M(SW)M \tag{4}$$

is a MC value, once it is multiplied by the left-hand term of expression (3), namely $\frac{n}{1'SW1}$

This allows the extraction from the n-by-n matrix of uncorrelated orthogonal components (Tiefelsdorf and Boots, 1995). This nonparametric approach has the aim of managing the presence of spatial autocorrelation by introducing a set of variables, the eigenvectors, able to catch the latent spatial association of georeferenced variables (Getis and Griffith, 2002). A set of candidate eigenvectors, that can be selected from the n eigenvectors on the basis of their MC values exceeding a pre-fixed threshold value of 0.25 (Griffith, 2003), can be used as predictors instead of not explicitly considered variables (Fischer and Griffith, 2008). In our case the candidate eigenvectors with MC > 0.25 are 27. Since the eigenvectors are both orthogonal and uncorrelated, a stepwise linear regression can be used to achieve this end.

The spatial model used is a transformation of the GWR model (Fotheringham *et al.*, 2002) proposed by Griffith (2008). The model exploits the spatial filters through the construction of a new set of variables created by the product between the spatial filters and the spatial variables.

In a regression model where Y is a n-by-1 vector that represents the dependent variable, β_j is the i_th regression coefficient and ε is an n-by-1 vector of the random error terms, the linear model with spatial filters incorporates a set P of regressors, $X_p = (p = 1,2, ..., P)$, with a k set of selected eigenvectors, $E_k = (k = 1,2, ..., K)$, which represent different spatial models, in order to consider the residual spatial autocorrelation in the dependent variable and has the following form:

$$Y = \beta_0 1 + \sum_{p=1}^{P} X_p \bullet 1\beta_p + \sum_{k=1}^{K} E_k \beta_{E_k} + \sum_{p=1}^{P}\sum_{k=1}^{K} X_p \bullet E_k \beta_{pE_k} + \varepsilon \tag{5}$$

where ● denotes element-wise matrix multiplication (i.e. Hadamard matrix multiplication), and each k identifies the eigenvector numbers that describe the attribute variable p, with K being the total number of these vectors. The regression coefficients, like in OLS model, stand for global values while the eigenvectors represent local modifications of global values. The first two terms (i.e. the global attribute variable coefficients) are multiplied by the vector 1, which also is a spatial filter eigenvector. More precisely, the global values are the coefficients needed to construct linear combinations of the eigenvectors, in order to obtain GWR-type coefficients. The sum of the first and third terms corresponds to the GWR intercept while the sum of the second and of the fourth elements represents the local parameters of the variables. Estimation of equation (5) needs to be followed by collecting all terms containing a common attribute variable and then factoring it out in order to determine its GWR coefficient. The GWR coefficients are linear combinations of a subset of the K eigenvectors, with those not in the subset having a regression coefficient value of 0; the GWR coefficients are n-by-1 vectors.

Estimation results

The global values (i.e. the average of parameters estimated for each region (local values)) of the parameters estimates for each model[8] are presented in Table 2. The convergence rate in model 1 is lower than in model 2: the adding of SF and CAP subsidies has a positive impact on the convergence process, by increasing significantly the global convergence rate, even if the values of their parameters are very low. In both models a negative and significant coefficient is associated to the variables *DISC_GVA* and *LL_LEAR*, while *EMP_SERV* has a positive and significant coefficient. The capital depreciation, as expected, negatively affects economic growth. The negative sign of the variable that catches the participants of lifelong learning programmes could be associated to the short term inability to productively employ high skilled workers. In the more developed regions the investments in lifelong learning are higher but, following

Table 2: Global parameters of spatial filtering models (standard errors are shown in parentheses).

Variables	Base model		Base model+ SF+ CAP subsidies	
Intercept	0.0185		0.0344	***
	(-0.0143)		(0.0129)	
GVA_EMP95 (β)	-0.0167	***	-0.0216	***
	(-0.0028)		(0.0025)	
DISC_GVA	-0.0179	***	-0.0141	***
	(-0.0019)		(0.0019)	
INV_GVA	0.0054	**	-0.00003	
	(-0.0026)		(0.0024)	
EMP_AGRI	0.0005		-0.0009	
	(-0.0005)		(0.0006)	
EMP_SERV	0.0264	***	0.0267	***
	(-0.0030)		(0.0030)	
LL_LEAR	-0.0045	***	-0.0059	***
	(-0.0008)		(0.0009)	
OB1_GVA			0.0008	***
			(0.0003)	
OB2-5_GVA			0.0002	
			(0.0002)	
SUBS_GVA			0.0010	***
			(0.0004)	
Test against heteroskedasticity				
Studentized Breusch-Pagan test	65.4328		44.249	
Spatial autocorrelation of residuals				
Moran's I	0.2926		0.5153	
Fit				
R-squared (adj.)	0.9163		0.9251	
	(0.8742)		(0.8873)	
Residual Std. errors	0.0034		0.0032	
AIC	-1686.539		-1709.072	

Significance: *** 1%, ** 5%, * 10%

[8] Table 2 shows the values of the coefficients of the variables before to add their associated eigenvectors.

the Solovian model, these regions grow more slowly, hence the negative value of the parameter. The ratio of employment in services sector has a positive and significant impact on economic growth, increasing the convergence rate. The SF for Objectives 1 and CAP subsidies are also positive and significant, while the SF for Objectives 2 and 5b are not significant. As shown in the introduction, the resources for Objectives 2 and 5b were very low and this may be the reason for their lack of effectiveness in terms of economic growth.

The impact on the convergence process of the CAP subsidies is a little greater than Objective 1 funds. This result is rather surprising and should be deeply investigated taking into account the structure of regional economies.

The two models show a high fit with both R^2 above 0.90 and a low Akaike Information Criterion (AIC) and residual sum of square (RSS). These indicators show a strong improvement in comparison with the OLS estimation (for each model the R^2 are about 0.40 and the AIC are higher). Furthermore, the residuals, in both models are not normally distributed[9], not spatially autocorrelated and homogeneous.

The dominant geographic scale of the collected eigenvectors associated with each variable gives us its geographic scale (Table 3). The sets of eigenvectors connected with the independent variables have mainly a local scale; the only exceptions are *EMP_SERV* and *LL_LEAR* in model 2 with a clear regional scale.

The local values, by quintile, of the local β-convergence rates are in Figures 4 and 5. In both models the macro-regions with similar values of rates of convergence do not coincide with the national boundaries emphasising the uniformity among neighbouring regions rather than within MS. In the two models the distribution of convergence rates among regions changes: while in the base model the regions with higher convergence rates do not coincide with the Objective 1 regions, in model 2 it happens; the only exception involves the Scandinavian regions which had already reached a high development level in 1995.

The density kernel of the local parameter of convergence is in Figure 6. In model 2 the top peak corresponds to higher convergence rates than in model 1. However we observe a double peak configuration mainly in model 1 in correspondence to 1% of divergence. In model 2 a just evident peak corresponds to a convergence rate of roughly 0.7% and 5%.

Table 3: Selected eigenvectors associated with the explanatory variables of each model.

Variables	Eigenvectors associated to explanatory variables: Global scale (MC > 75) from eig. 1 to 4	Regional scale (75 > MC > 50) from eig. 5 to 11	Local scale (50 > MC > 25) from eig. 12 to 27
Base model			
Intercept	E1	E8	E13, E23
GVA_EMP95 (β)	-	E8	E26
DISC_GVA	E1	E10	E12, E26
INV_GVA	-	E5, E10	E17, E20, E21, E23, E25, E26
EMP_AGRI	E1, E2, E3	E7, E8	E14, E17, E21, E25, E27
EMP_SERV	E1	E5, E11	E16, E20, E21, E22
LL_LEAR	-	E5, E7, E10, E11	E12, E16, E20, E23
Base model + SF + CAP subsidies			
Intercept	E2	-	-
GVA_EMP95 (β)	-	E7	E13, E18, E23
DISC_GVA	E1, E2	-	E18, E26
INV_GVA	E2	-	E23, E25
EMP_AGRI	E2	E8, E11	E18, E25, E26, E27
EMP_SERV	E1	E11, E12	-
LL_LEAR	-	E5, E7, E11	-
OB1_GVA	-	E6, E7	E23, E24
OB2-5_GVA	E3	-	E21, E23, E27
SUBS_GVA	-	E6, E11	E18, E24, E26

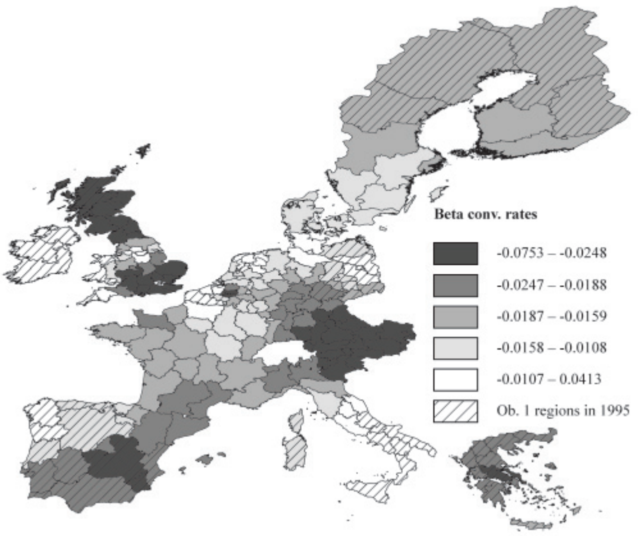

Figure 4: Spatial distribution by quintile ranges of the local β-convergence rates of GVA per worker in the Base model (EU NUTS2 regions).

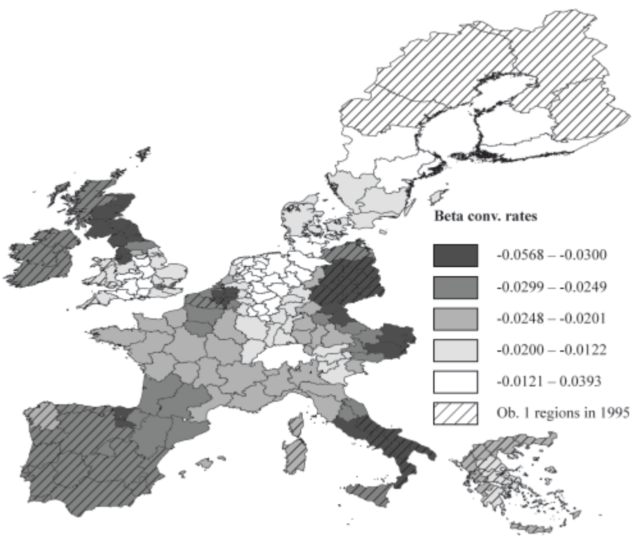

Figure 5: Spatial distribution by quintile ranges of the local β-convergence rates of GVA per worker in the Base model + SF + CAP subsidies (EU NUTS2 regions).

[9] It is interesting to observe that the used spatial weights matrix is able to weigh the regression eliminating hetehoskedasticity. Using other spatial weights matrix it often happens that only spatial autocorrelation is corrected while the problem of non-homogeneity of error terms is not solved.

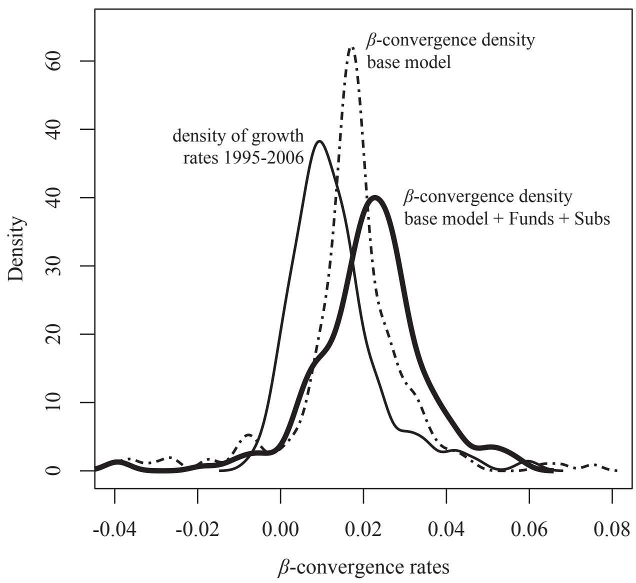

Figure 6: Density kernel of estimated convergence rates.

The Regression Discontinuity analysis

As already seen, the previous analyses on the effectiveness of EU Regional Policy for reducing gaps among EU regions, are unable to reach unambiguous conclusions. This depends on several factors: different periods covered, different techniques used, different empirical and convergence models adopted.

The evaluation of the impact of CP on growth and on convergence processes involves considerable methodological problems, related both to the availability of time series data comparable across countries, and to the difficulty of estimating the counterfactual hypothesis, that is the economic growth achieved in the absence of the Objective 1 SF. In addition, it is not easy to separate the effects of the other factors influencing growth.

As argued by Morton (2009) a counterfactual analysis is essential to identify the effects on regional economies of the EU policies. This approach has been little used, especially when the goal was to compare the Objective 1 regions (defined as 'treated' because they receive the Objective 1 SF) to non-Objective 1 regions ('not treated'). A helpful technique is the Regression Discontinuity (RD), which allows assessing the impact of some policies in case of non-experimental design, i.e. when it is not possible to conduct randomised experiments to determine the effects of these policies. The RD estimates the effects of a policy (in our case the regional parameter of β-convergence rate, the outcome of the model) when the treatment allocation is determined by the level of an observed variable (per capita GDP in 1995, the forcing variable), and in particular whether or not this variable exceeds a certain threshold (cut-off point).

The basic concept of RD is that the average score of the subjects (in our study the EU regions) which fall marginally above (below) the cut-off point, is a valid comparison for the group which falls marginally below (above) the threshold. If the association of the forcing variable and the outcome is continuous, any discontinuity in the forcing variable at the cut-off point can be interpreted as empirical evidence of the effect of the random treatment: the presence or absence of the Objective 1 SF (Imbens and Lemieux, 2008).

The discontinuity in the RD is based only on the relationship between the outcome and the cut-off point. As a result, close to the cut-off point, we may compare the units in the treated and untreated groups[10]. Moreover, this can be extended to the regions with probability to be close to the cut-off (Lee, 2008). From a methodological point of view, the inference on the RD is comparable with the results of randomised experiments.

In our analysis the RD approach is used for estimating the effects of Regional Policy on the convergence process of the EU regions (see Lee and Lemieux (2009) for a survey on the RD and its main applications in economics). Regions whose per capita GDP is less than 75% of the EU average (Objective 1) are compared with those above the 75% threshold (not eligible for funding); the forcing variable is regional GDP per capita, the cut-off point is the 75% threshold and the treatment is EU Objective 1 funds[11]. Let us here remark that, in line with the basic idea of RD, the treatment (i.e. the Objective 1 funds) is assumed to depend only on whether in region *i* the level of GDP per capita is below the fixed threshold. This is a case of 'sharp design': the treatment only depends on the level of GDP per capita (Imbens and Lemieux, 2008).

In our case the hypothesis is that the average outcome for regions just above the cut-off point can represent a valid counterfactual for those just below the threshold. The comparison of the β-convergence rates of regions receiving EU funds with that of unassisted regions at the cut-off point allows us to identify the locally average policy effect at the threshold. Nevertheless, in our analysis, the RD suffers two main disadvantages. Firstly, the low number of observations close to the threshold determines a trade-off between the size of the interval in the neighbourhood of the cut-off point and the accuracy of the statistical estimates. Secondly, the convergence rates present a high variability with respect to the initial level of the GDP per capita. The limited number of observations close to the cut-off point might identify a group of regions with features that differ markedly from those of unassisted regions, compromising the accuracy of estimates. In the light of these problems, at this stage, we only propose a graphical analysis.

Lee and Lemieux (2009) argue that a simple way to evaluate the effects of the treatment (the presence of Objective 1 funds) is to plot the relationship between the outcome variable (the regional β-convergence rates) and the forcing variable (the levels of GDP per capita) per region, on either sides of the cut-off point. If there is no visual evidence of a discontinuity in the graph, it is unlikely that more sophisticated regression methods will yield a significant policy effect.

[10] Lee (2008) shows that the RD is equivalent to a local random assignment around the cut-off.

[11] According to this division, 56 regions are below the threshold of 0.75 and 148 above. For coherence with the previous analysis, the calculation of average GDP in PPS was carried out using the Cambridge Econometrics database whose data cannot be fully compatible with those used by EU in the determination of the Objective 1 eligible regions. According to our calculations 7 of the 56 regions below the threshold were not eligible for the Objective 1, while, among the 148 regions above 75% there were 14 regions: (i) eligible for the Objective 1 only in 2000-2006, (ii) phasing-out in 1994-1999 or in 2000-2006; (iii) with only part of their territory eligible for the Objective 1.

Table 4: Average incidence in Objective 1 and other EU-15 regions: (i) SF Objective 1 (1994-2006) per inhabitants and as percentage of total GVA; (ii) CAP subsidies (1995-2006) per person employed on agriculture and as percentage of total GVA.

		Obj. 1 funds 1994-2006 / inhabit. 1995 (euro/inhabit.)	CAP subsidies 1995-2006 / agric. empl. 1995 (euro/agr. empl.)	Obj. 1 funds 1994-2006 / GDP 1995 (%)	CAP subsidies 1995-2006 / GDP 1995 (%)
Below Cut-off point	56 regions	2,435	56,308	22.50	18.10
	only Ob. 1 regions	2,783	56,039	25.80	19.30
Above Cut-off point	148 regions	107	68,863	0.62	6.88
	only non Ob. 1 regions	0	67,672	0	6.10

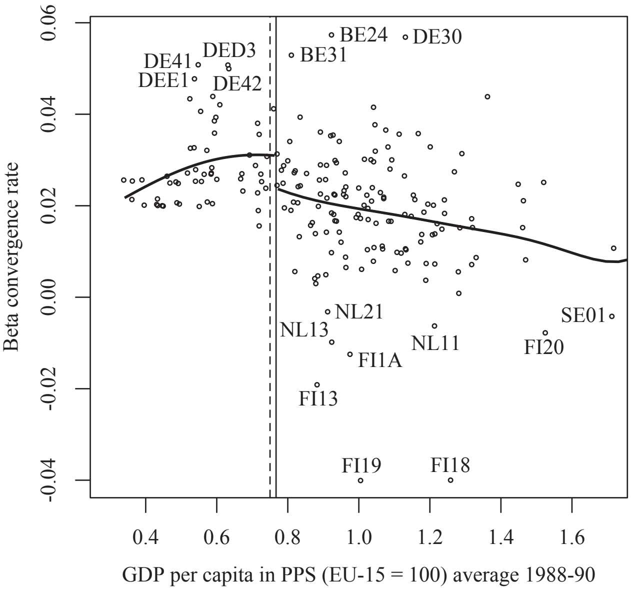

Figure 7: A comparison of the β-convergence rates of Objective 1 and other EU-15 regions (Base model + SF + CAP subsidies).

The results of the nonparametric technique proposed by Bowman *et al*. (2006) are shown in Figure 7. The regional β-convergence rates of the model 2 are plotted against the level of GDP per capita (in PPS), average 1988-1990[12], standardized with respect to the EU-15 mean value (equal to 100). The presence of discontinuity is significant (p-value 0.033) at the cut-off point 0.767 (solid line), which is very close to 0.75 (dashed line), the separation level of 'treated' and 'not treated' regions. On average, regions with GDP per capita less than 0.75 present higher β-convergence rates than other EU-15 regions. The existence of a clear discontinuity at the cut-off point is supported by the graph. The non-parametric regression line shows a negative jump moving from regions with GDP per capita less than 0.75 to the ones with GDP per capita above the 75 per cent threshold.

Finally, using this division between regions, we calculated the total SF Objective 1, for the period 1994-2006, per 1995 inhabitants and the incidence on 1995 total GVA; the total of CAP subsidies (I and II pillar), for the period 1995-2006, per 1995 agricultural employee and the incidence on 1995 total GVA (Table 4). The two groups of regions are characterised mainly by the presence, or absence, of the Objective 1 SF, while the CAP subsidies for agricultural employment are comparable between the two groups of regions, although their impact on total GVA, as expected, is much higher in Objective 1 regions.

Discussion

Our study allows some final considerations. In terms of β-convergence rates, our results are in line with the ones of Ederveen *et al.* (2006) and show an improvement in comparison with the study of Cappelen *et al.* (2003). Furthermore, the analysis confirms the results obtained in other recent studies (e.g. Arbia *et al*., 2010). In the period 1995-2006 a weak convergence process of labour productivity occurred in the 204 EU-15 regions analysed, although with significant differences among the European regions.

According to the results of model 2 the relative positions of the regions in term of convergence rates change with respect to model 1: in model with SF and CAP subsidies the more economically disadvantaged regions at the beginning of the considered period show (with respect to the other regions) the highest relative β-convergence rates. This is in line with what is suggested in previous studies on the effects of CP, in particular Leonardi (2006). In addition to this finding we must add that, with respect to the base model where the regions with parameter of β-convergence less than -0.025 number only 39, in model 2 we observe that all regions with GDP per capita lower than 75 (Objective 1 regions) increase, in absolute terms, their convergence rates: the 80 regions with β-convergence rates less than -0.025 are almost always located in peripheral areas of the EU. They include nearly all of the Austrian and Belgian regions, a number of German regions, especially those belonging to the former DDR, many Spanish regions, four regions of France, Irish regions, almost all the regions of central and southern Italy, a Dutch region, the Portuguese ones and half of the UK regions.

These aspects confirm the effectiveness of the two support measures but do not allow to determine which is the most appropriate without looking at the regional economic structure.

The number of regions that diverge is notably reduced (from 17 to 9) when CAP and SF are included.

Through the Regression Discontinuity approach it is possible to compare the results of less-favoured regions (mainly Objective 1) with those of the most developed. First of all Objective 1 regions reached a higher speed of convergence but the contribution of SF to the convergence process, in relation to regionally targeted Objectives 1, 2 and 5b, is not unequivocal. Only Objective 1 SF has a positive and significant impact, although very limited, while the contribution of Objectives 2 and 5b SF is not significant. The absence of significance for these SF can be explained by looking

[12] To define regions receiving SF the indicator of GDP per capita is measured by the EC in the last three years at the time of closing of the negotiations. For the period 1994-1999, the years were: 1988,1989,1990.

from one side at the limited amount of resources allocated to these regions, and from the other at the eligibility criteria of Objective 2 areas: although the 'regionalised' target, it differs among different regions and countries because the eligibility depends on a population ceiling and other specific criteria. This means that the socio-economic conditions are not uniform across eligible EU regions.

Contrary to expectations, CAP subsidies have a positive impact on the convergence process little bit higher than Objective 1 funds. This result is not a foregone conclusion. In absolute terms the highest CAP subsidies refer to regions outside Objective 1, where the impact of the CAP subsidies on economic growth at territorial level may be almost irrelevant when we consider only the primary sector. On the other hand this result confirms the findings of Montresor and Pecci (2008) but also gives new and important indications about the interpretation of the effects of CAP subsidies. If the analysis moves to the complex system of interdependencies between agriculture and the food industry, it can be inferred that the impact of CAP subsidies may be positive also for the less developed economies, as the increasing relationships allow a better exploitation of agricultural production. We could here recall a sort of 'big push' due to the indirect effect of CAP subsidies on less developed economies: the spatial spillovers exerted by (not necessarily poor) regions may help the other regional economies to overcome deficiencies in private incentives that prevent firms from adopting modern production techniques and achieving scale economies. As a consequence the effects of CAP subsidies are not only restricted to the rural and agricultural sector, but they affect the entire economy.

In light of these results, the recent EC budget proposal (EC, 2011) to not significantly reduce the resources for the CAP from 2014 to 2020 and to propose a change designed to lead to a fairer and more equal system of support across the EU and to ensure a more equal distribution of direct support, suggests that, in the future, these positive effects on growth processes of EU regions will be further developed.

It can also be assumed that in less economically advanced regions (to follow Cappelen *et al.*, 2003) the CAP subsidies, even if smaller, since the agri-food sector is important in their economies, have been a significant support to economy of those regions.

Under a methodological profile the spatial econometric technique used in our study allows a clear progress for analysing the convergence process and the estimation of local β-convergence rates. This technique permits, *inter alia*, examining the convergence process without identifying *a priori* the type of convergence, i.e. conditional or convergence clubs. As a consequence, for the interpretation of the results, beside the structure of the economies, we must take into account the existence of spatial interactions related to spatial weights matrix. In addition to the SF impact, in fact, there are the effects induced in the economies of each region from the economies of surrounding regions.

Finally, these results show that the path for analysing the economic convergence in the EU is still long. In particular, doubts about the ability of the SF to ensure sustainable economic growth and to reduce the gaps between centre and periphery of Europe still seem to be well founded.

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Appendix

The EU NUTS 2 regions in the sample.

NUTS	β model 1 (%)	β model 2 (%)
AT11	-6.32	-3.90
AT12	-6.76	-4.09
AT13	-7.53	-4.35
AT21	-3.32	-2.71
AT22	-4.10	-3.11
AT31	-3.41	-2.92
AT32	-3.26	-2.64
AT33	-3.58	-1.81
AT34	-2.59	-2.01
BE10	-2.57	-5.38
BE21	-1.93	-3.27
BE22	-1.72	-1.63
BE23	-0.79	-3.51
BE24	-2.91	-5.68
BE25	-0.50	-2.97
BE31	-2.77	-5.25
BE32	-1.28	-3.54
BE33	-1.64	-1.33
BE34	-1.58	-1.56
BE35	-1.86	-2.86
DE11	-2.43	-2.10
DE12	-2.17	-1.72
DE13	-2.00	-1.77
DE14	-2.48	-2.03
DE21	-3.05	-2.46
DE22	-2.91	-2.95
DE23	-2.60	-3.17
DE24	-2.36	-3.26
DE25	-2.52	-2.73
DE26	-2.28	-2.28
DE27	-2.76	-2.23
DE30	0.74	-5.63
DE41	0.48	-5.04
DE42	-0.20	-4.95
DE50	-1.30	-0.83
DE60	-0.82	-0.24
DE71	-2.20	-1.52
DE72	-2.12	-1.43
DE73	-2.01	-1.74
DE80	-1.18	-2.82
DE91	-1.65	-2.10
DE92	-1.49	-1.05
DE93	-0.91	-0.32
DE94	-1.14	-0.66
DEA1	-1.44	-0.57
DEA2	-1.59	-0.74
DEA3	-1.34	-0.62
DEA4	-1.65	-1.07
DEA5	-1.70	-0.97
DEB1	-1.75	-1.05
DEB2	-1.55	-0.89
DEB3	-1.93	-1.37
DEC0	-1.62	-1.12

NUTS	β model 1 (%)	β model 2 (%)
DED1	-1.82	-4.30
DED2	-1.60	-3.56
DED3	-1.46	-5.03
DEE1	-1.36	-4.74
DEE2	-1.74	-4.03
DEE3	-1.53	-3.19
DEF0	-1.07	-0.80
DEG0	-2.02	-3.24
DK	-1.45	-1.53
ES11	-0.81	-2.48
ES12	-1.11	-2.52
ES13	-1.36	-2.70
ES21	-1.42	-3.06
ES22	-1.66	-2.97
ES23	-1.52	-3.09
ES24	-2.08	-2.69
ES30	-2.39	-2.76
ES41	-1.58	-2.67
ES42	-2.60	-2.70
ES43	-1.89	-2.55
ES51	-2.07	-2.52
ES52	-2.46	-2.57
ES53	-1.96	-2.37
ES61	-2.16	-2.49
ES62	-2.49	-2.52
FI13	-1.70	1.87
FI18	-1.69	3.93
FI19	-1.68	3.93
FI1A	-1.69	1.21
FI20	-1.65	0.75
FR10	-1.22	-2.50
FR21	-1.47	-2.19
FR22	-0.85	-2.69
FR23	-1.78	-2.23
FR24	-1.61	-2.40
FR25	-1.96	-2.07
FR26	-1.57	-2.24
FR30	-0.53	-2.86
FR41	-1.57	-1.57
FR42	-1.82	-1.62
FR43	-1.69	-1.98
FR51	-1.82	-2.25
FR52	-1.62	-2.06
FR53	-1.81	-2.43
FR61	-1.86	-2.56
FR62	-1.98	-2.55
FR63	-1.80	-2.48
FR71	-1.75	-2.22
FR72	-1.76	-2.41
FR81	-1.91	-2.44
FR82	-1.78	-2.24
FR83	-1.48	-2.27
GR11	-1.88	-2.02

NUTS	β model 1 (%)	β model 2 (%)
GR12	-1.98	-2.03
GR13	-1.97	-2.08
GR14	-2.30	-1.99
GR21	-1.88	-2.13
GR22	-1.93	-2.14
GR23	-2.45	-2.01
GR24	-2.53	-1.95
GR25	-2.41	-2.00
GR30	-2.26	-1.98
GR41	-1.92	-2.00
GR42	-1.82	-2.04
GR43	-1.88	-2.06
IE01	4.13	-2.78
IE02	3.73	-2.68
ITC1	-1.91	-2.15
ITC2	-1.89	-2.12
ITC3	-1.84	-2.16
ITC4	-2.23	-2.01
ITD1	-3.75	-1.61
ITD2	-3.28	-1.66
ITD3	-2.73	-1.94
ITD4	-2.85	-2.38
ITD5	-1.79	-2.13
ITE1	-1.13	-2.32
ITE2	0.73	-2.88
ITE3	0.57	-2.87
ITE4	0.93	-3.00
ITF1	1.81	-3.38
ITF2	2.65	-3.78
ITF3	2.62	-3.83
ITF4	3.07	-4.18
ITF5	3.54	-4.35
ITF6	0.91	-3.25
ITG1	-0.43	-2.68
ITG2	-1.39	-2.31
LU	-1.51	-1.08
NL11	-0.01	0.60
NL12	-0.79	-0.42
NL13	0.17	0.95
NL21	-0.43	0.29
NL22	-1.08	-0.48
NL23	-1.00	-0.58
NL31	-1.26	-1.22
NL32	-1.24	-1.38
NL33	-1.26	-2.18
NL34	-0.87	-2.99
NL41	-1.55	-1.72
NL42	-1.58	-0.98
PT11	-0.87	-2.53
PT11	-0.87	-2.53
PT15	-2.07	-2.51
PT15	-2.07	-2.51

NUTS	β model 1 (%)	β model 2 (%)
PT16	-1.38	-2.55
PT16	-1.38	-2.55
PT17	-1.97	-2.58
PT17	-1.97	-2.58
PT18	-2.08	-2.63
PT18	-2.08	-2.63
SE01	-1.62	0.39
SE01	-1.62	0.39
SE02	-1.59	-0.39
SE04	-1.50	-1.83
SE06	-1.60	-0.75
SE07	-1.63	-0.73
SE08	-1.67	-0.11
SE09	-1.55	-1.39
SE0A	-1.55	-1.52
UKC1	-4.14	-3.52
UKC2	-4.58	-3.59
UKD1	-3.29	-3.63
UKD2	-1.18	-3.55
UKD3	-1.07	-3.74
UKD4	-1.78	-4.12
UKD5	-1.45	-3.91
UKE1	-1.46	-1.70
UKE2	-1.84	-2.70
UKE3	1.14	-1.39
UKE4	-0.19	-2.39
UKF1	0.79	-1.09
UKF2	-2.06	-0.99
UKF3	-1.88	-1.43
UKG1	-2.74	-0.51
UKG2	-1.80	-1.84
UKG3	-2.44	-0.60
UKH1	-3.11	-1.66
UKH2	-2.79	-1.49
UKH3	-3.60	-1.66
UKI1	-1.01	-2.78
UKI2	-1.00	-2.79
UKJ1	-3.20	-0.88
UKJ2	-2.56	-1.81
UKJ3	-3.12	-1.06
UKJ4	-3.23	-1.81
UKK1	-2.85	-0.76
UKK2	-2.15	-1.21
UKK3	-0.71	-1.89
UKK4	-0.95	-1.67
UKL1	-0.88	-1.90
UKL2	-1.36	-1.86
UKM1	-3.79	-3.12
UKM2	-4.33	-3.54
UKM3	-3.37	-3.38
UKM4	-2.97	-2.99
UKN0	1.65	-2.75