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Cross-national Neighbouring Effects on European Regional Specialization

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ABSTRACT *In undertaking an analysis of neighbouring effects on European regional patterns of specialization, this paper makes two main contributions to the literature. First, we use a spatial weight matrix that takes into consideration membership of an EU cross-border regional association. We then compare our results with those obtained using a contiguity matrix and constitute an upper bound for our parameter of interest. In a further stage, we divide the CBR associations on the basis of their long-standing and the intensity of their cooperation to determine whether the association type has a significant impact. Second, we examine the sensitivity of our results to the use of alternative relative specialization indices.*

Effets de voisinage transfrontière sur la spécialisation régionale en Europe

RÉSUMÉ *En entreprenant une analyse des effets de voisinage sur les configurations de spécialisation régionales européennes, la présente communication contribue de deux façons principales à la littérature. En premier lieu, nous utilisons une matrice de ponde'ration spatiale, qui tient compte l'appartenance à une association régionale transfrontière de l'UE. Nous comparons ensuite nos résultats avec les résultats obtenus à l'aide d'une matrice de contiguïté, et nous nous en servons pour constituer une limite supérieure pour le paramètre qui nous intéresse. A partir de là, nous répartissons les associations CBR en fonction de leur duré et de l'intensité de leur coopération, afin d'établir la mesure dans laquelle le type d'association présente un impact significatif. Deuxièmement, nous examinons la sensibilité de nos résultats à l'emploi d'indices de spécialisation alternatifs.*

Efectos de la colindancia entre naciones sobre la especialización regional europea

RESUMEN *Analizando los efectos de la colindancia sobre los patrones de especialización regionales europeos, este trabajo realiza dos aportes importantes a la bibliografía especializada. En el primero de*

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ellos, utilizamos una matriz de ponderación espacial que tiene en cuenta la pertenencia de una asociación regional transfronteriza comunitaria. Posteriormente, comparamos nuestros resultados con los obtenidos con una matriz de contigüidad y constituimos un límite superior para nuestro parámetro de interés. En una fase posterior, dividimos las asociaciones regionales transfronterizas con base en su perduración y su grado de cooperación para determinar si la asociación tiene un efecto significativo. En el segundo, analizamos la sensibilidad de nuestros resultados en lo que respecta al uso de índices relativos de especialización alternativos.

跨国毗邻效应对欧洲地区专业化的影响

摘要：本文分析了毗邻效应对欧洲地区专业化模式的影响，对这方面的研究主要做出了两个贡献。首先，笔者采用了将欧盟跨边境地区协会的成员纳入考虑范围的空间加权矩阵，然后将结果与通过邻近矩阵获得的结果对比，构成了感兴趣参数的上界。在下一个阶段，笔者将 CBR 协会按持续时间和合作强度分类，确定该协会类型是否有重要影响。其次，笔者检查了结果对使用其他相关专业化指数的敏感性。

KEYWORDS: *Regional specialization; European regions; spatial econometrics*

JEL CLASSIFICATION: R11; R12

1. Introduction

The spatial distribution of regional economic activity in the European Union has been the focus of growing research interest. Spatial econometric techniques have been applied to examine the impact that externalities in neighbouring regions have on regional sectorial specialization (Ezcurra *et al.*, 2006; Mora *et al.*, 2006; Mora & Moreno, 2010). These empirical contributions have proved the relevance of European regional contiguity in explaining regional sectorial specialization even using cross-sectional data or short panels.

Specifically, this empirical analysis explores cross-border neighbouring effects on regional specialization in the European Union of 15 member states (EU-15). Our main goal is to explore to what extent European regional specialization is influenced by neighbouring cross-border regions presenting common institutional links. In fact, four specific features of our analysis are worth highlighting: (i) we draw on information for regions integrated in Cross Border Region associations (hereafter CBRs) to construct a spatial weight matrix. This is then used to examine neighbouring effects and integration effects by estimating a spatial error model; (ii) we undertake a sensitivity analysis of our results based on the choice of specialization measure; (iii) we explore by means of a longer panel data approach; and (iv) we contribute to the ongoing debate on territorial cohesion.

First we adopt Arbia & Fingleton's (2008) suggestion regarding the need to focus future empirical research on the arbitrary selection of weight matrices. Specifically, we seek to examine cross-border influences by considering solely the impacts of regional associations. As a result, the overall neighbouring impact on regional specialization is underestimated. Results from a spatial weight matrix that accounts for all neighbouring regions might represent an upper limit for our estimates using CBR information. However, this impact is mis-estimated when interdependence is not included (Franzese & Hays, 2007). In addition, this analysis allows us to examine the effects of European integration on European regional specialization. *A priori*, since CBRs are formed by cross-country regional economies, we expect the specialization levels of these economies to be less prone to the influence of foreign contiguous neighbours than they are to that of their national counterparts alone. Nevertheless, we also expect European integration to reduce this border effect. To ascertain this effect, we only consider those regions forming part of a CBR association in this analysis.

Second, the suitability of the specialization index selected has been discussed by several authors when determining specialization levels (Combes & Overman, 2004; Bickenbach & Bode, 2008). According to Bickenbach & Bode (2008), three features unambiguously define an inequality measure: regional weights, the reference distribution and the projection function. However, the authors also note that in any empirical investigation, the specification of each feature should be determined by the research goal and should take into consideration the specificities of the available data. An additional matter is the modifiable areal unit problem, which has been consistently tackled in recent literature (Brülhart & Traeger, 2005). Our proposal is to exploit more similar regional units. Nevertheless, for reasons of robustness and since our inferences may be affected by the presence of outliers in the selected measure, we verify whether choosing alternative specialization indices might affect the estimated impact of neighbouring regions. We therefore also use the mutual information index, the dissimilarity specialization index and the Krugman specialization index.

Third, by using CBRs to explore cross-national neighbouring effects on regional specialization in the European Union, we contribute to the current debate on territorial cohesion (European Commission, 2008; Barca Report, 2009). The impact of CBRs in terms of specific outputs is difficult to identify. As Mirwaldt *et al.* (2009) point out, both the small scale of their financial resources and the shortcomings in their monitoring systems and data collection complicate the identification of quantitative impacts.

Three results can be highlighted from our empirical analysis. First, we confirm neighbouring effects on regional specialization. However, the estimated spatial impact is found to be lower when using cross borders, i.e. in the presence of an institutional agreement. In other words, the impact exerted by associated regions on each other in terms of European regional relative specialization is lower than that exerted by neighbouring regions. Second, the greater the intensity of cooperation recorded between CBRs or the greater the number of years of association, the higher the impact. Thus, by accounting for highly intense cooperation and long-standing links between CBRs we obtain virtually the same autocorrelation effect as when using all the information on contiguity. Third, we use alternative specialization indices with sufficient statistical variation. We find that neighbouring impact presents little sensitivity to the choice of specialization index.

The remainder of this paper is structured as follows. The next section reviews the factors underpinning the constitution of CBR associations, while the third section presents the data and the econometric specification. The fourth section reports the results and the final section contains a brief discussion of our overall findings.

2. European Cross-border Regions

It is becoming increasingly difficult today to find European regions or municipalities that do not participate in cooperation projects with territories elsewhere in Europe. Roughly speaking, two types of interregional project can be distinguished: cooperation without any requirement of geographical continuity and cooperation based on proximity. The former has resulted primarily in the creation of lobbies and groups for exchanging local experiences. International forums such as Eurocities and the Assembly of European Regions have been established, along with industrial organizations, such as the Assembly of European Wine Regions and the *Asociación de Regiones Europeas con Tradición Industrial*, and interregional organizations such as the 'Four Motors of Europe' (Catalonia, Baden-Württemberg, Lombardy and Rhône-Alpes). Cooperation of this type, however, is not taken into account in this article.

Cooperation projects based on proximity—i.e. between territories on either side of Europe's internal or external borders—include both the Euroregions and the work communities. The former have been widely developed among the contiguous territories of the Rhine basin, but typically include few regions. The latter, which include the Western Alps and Galicia–Northern Portugal, typically group together more than four regions. The number of such CBRs in the EU-15 has doubled since 1990, with 10 having been created before then and 14 since (Perkmann, 2003; INTERACT, 2007). Figure 1 shows the regions forming CBR associations.

Territorial cooperation among the EU-15 continues, in the main, to be *low-intensity*. According to Perkmann (2003), at the beginning of this century fewer than eight CBRs maintained a permanent secretariat and had drawn up development plans and comprehensive cooperation schemes. Most *high-intensity* CBRs were to be found in the European *Pentagon* and in the Scandinavian countries.

Evidence suggests that there have been two main driving forces behind the emergence and proliferation of CBRs across Europe. On the one hand, the Council of Europe (1995) has been an active force in the legal arena, helping to establish a framework for non-central government cooperation across borders; on the other hand, the European Union has been the driving force in the financial arena, providing economic support for such initiatives, in particular backing the launch of the Community Initiative INTERREG in 1990. Functional links do not appear to have played a role in the emergence of CBRs and most of their projects are conducted in institutional, cultural and environmental arenas as opposed to boosting potential economic synergies (Church & Reid, 1996; Brunn & Schmitt-Egner, 1997; Stryjakiewicz, 1998; Krätke, 1999; Koschatzky, 2000; Perkmann & Sum, 2002; Perkmann, 2003; Meijers & Romein, 2003; Kramsch & Hooper, 2004; Knippenberg, 2004; Matthiessen, 2005).

However, today there are increasing expectations that CBRs should strive to develop functional economic links. Territorial cooperation is now an objective of the EU's Social and Economic Cohesion Policy for 2007–2013 and is a key policy instrument for developing the EU's territorial cohesion (Garcia-Duran, 2005; European Commission, 2008; Barca Report, 2009). A content analysis of the regulations and other documents related to cross-border cooperation shows that there has been a shift in the justifications put forward for receipt of financial support (Garcia-Duran *et al.*, 2009). Thus where previously support was sought for

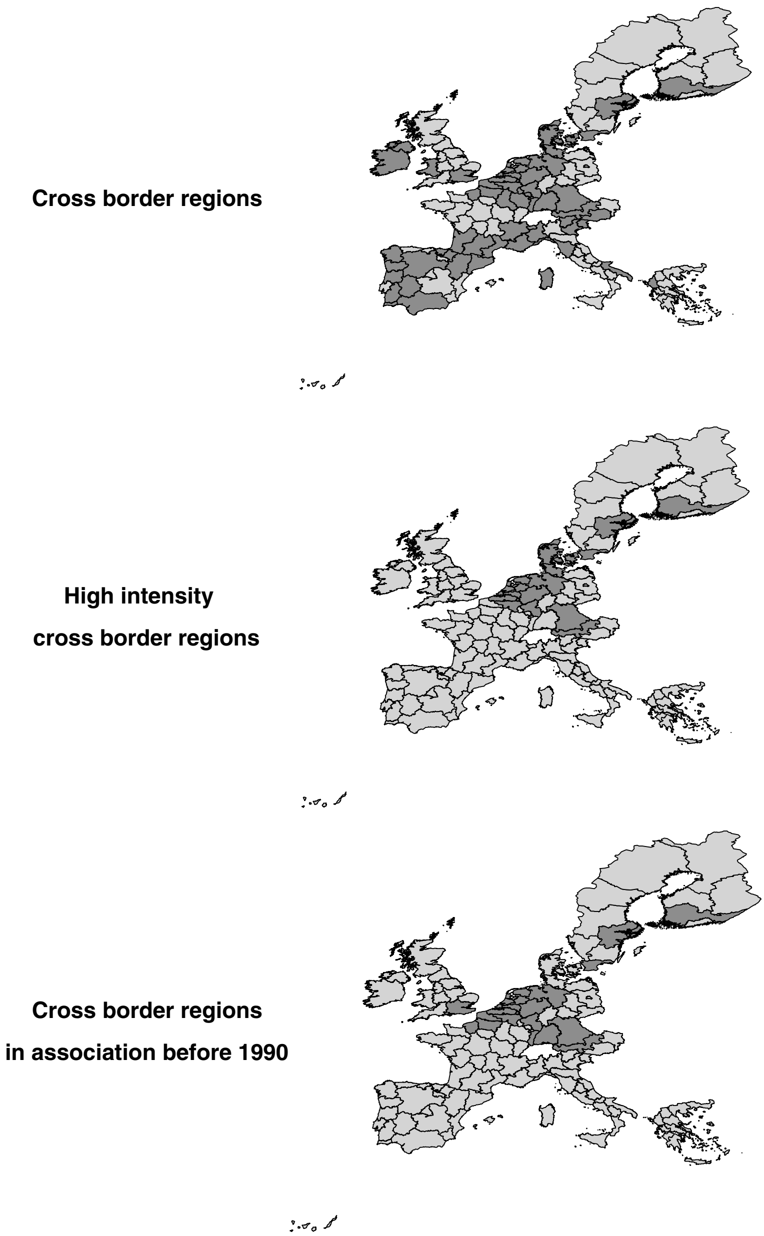

Figure 1. European regional economies in CBR associations.
Note: Regions in dark are the ones associated into CBRs.

underdeveloped regions facing a range of economic problems, support today is required to stimulate the economic growth of the EU. In INTERREGS I (1990–1993) and II (1994–1999), the primary goals were to promote the economic development of regions suffering the effects of their peripheral border location and to provide them with compensation for the loss of income resulting from the elimination of internal customs within the EU. From INTERREG III (2000–2006) onwards, there have been greater attempts to promote the territorial cohesion of the EU, without which economic and social integration are severely hindered. Thus there is now a need to estimate the degree of economic functionality achieved (or achievable) by CBRs.

3. European Regional Specialization

3.1. Data and Control Variables

We use an EU-15 regional sample for the period 1992–2007 and have chosen the NUTS-2 level as the spatial unit for performing our analysis, given that this is the highest level of disaggregation for which statistical information is available. However, in Europe there is in fact a considerable degree of heterogeneity in the size and scope of this administrative division. In this regard, Combes & Overman (2004) have stated that measures should be comparable across spatial scales. Their concern derives from the fact that spatial inequality measures are sensitive to the definition of regions because of the presence of either geographic or economic size differences. For this reason, our sample comprises regions from the NUTS 0, 1 and 2 classifications, thereby enabling us to achieve a more homogeneous database with respect to the geographical size of the European regions. The result is a division of Europe into 130 sub-national units (which we refer to simply as regions). NUTS-2 regions are used for Greece, Finland, France, Italy, Portugal, Spain and Sweden, and NUTS-1 regions for Austria, Belgium, Germany, the Netherlands and the United Kingdom. We consider Ireland, Denmark and Luxembourg as single regions (NUTS-0).

For the computation of specialization, we use annual employment levels (in thousands). We use a panel of European regional data from the Cambridge Econometrics database. The sector classification considered for data on employment is NACE R17 (Classification of Economic Activities in the European Community aggregated to 17 sectors, which is the highest sectorial disaggregation for which European regional statistical information is available).

Although analysing the impact of neighbouring regions is our main goal, in this paper we also need to control for other variables. Table 1 shows the sources of statistical information for our control variables. For most of them, the statistical information is taken from the Cambridge Econometrics database. These variables are introduced into the empirical specification with a one-period lag so as to avoid contemporaneous effects. The literature on the determinants of specialization at regional level places the stress on several determinants that will be analysed in this paper: human capital and the existence of a specialized regional labour pool, the presence of agglomeration economies, regional investments and innovation activities.

First, the impact of a specialized regional labour pool was taken into account (McCann, 2001). For regional labour pool effects, we use the levels of regional compensation per employee. Second, Kalemli-Ozcan *et al.* (2003) point out that human capital may be a better indicator of development than per capita GDP since, among other reasons, education improves the monitoring of managers. For this purpose, we consider human capital endowment levels measured through the proportion of people attaining higher education.[1] Third, Brülhart & Mathys (2008) claim that theoretical approaches consider agglomeration as a process that leads to the spatial concentration of economic activity. In order to study the effects of agglomeration we include controls such as market potential[2] and regional

Table 1. Definition and sources of covariates

	Definition	Source
Investment levels	Total regional investment expenditure in millions 1995 Euro	Cambridge Econometrics Database
Compensation per employee	Average regional compensation levels per employee in Euro	Cambridge Econometrics Database
Market potential	Regional ΣGDP over distance values between two specific regions	Own computation based on Cambridge Econometrics Database & geographical distance data
GDPpc	Regional GDP in per capita terms in millions 1995 Euro	Cambridge Econometrics Database
Number of patents	Regional number of patents in percentage terms to regional GDP values	CRENOS & own computations
% Agricultural sector	Regional share of agriculture activity in regional GVA	Cambridge Econometrics Database
Human capital	Share of labour force attaining medium and higher educational endowments	Computations from the European Labour Force Survey
Density of population	Regional density = number of inhabitants by region by squared km	Cambridge Econometrics Database
Human capital*Adhesion95	Interaction of human capital variable at the regional level with a dummy = 1 when region belongs to countries enlarging EU in 1995	Own computations

population density. An additional effect is expected from the non-linear relationship between specialization and the level of development (Imbs & Wacziarg, 2003). This leads us to introduce regional GDPpc to proxy regional size, where we test for a non-linear impact. Fourth, other regional features such as investments and innovation activities have been taken into account. It is sensible to think that large innovative regions, or those with high investment activities, will tend to impact significantly on the local development of industrial clusters, so that a higher specialization level can be expected in them. We proxy for regional technological characteristics by using investment levels and for innovation activity by means of the number of patents in each region as a percentage of GDP.[3] Finally, the level of specialization in the agricultural sector is used to investigate to what extent the specialization levels of the sample regions are driven by agriculture.

3.2. Specialization Measurement

European regional specialization patterns have previously been explored in the regional analysis literature (Molle, 1996; Hallet, 2002; Ezcurra *et al.*, 2006; Mora *et al.*, 2006; Cutrini, 2010; Mora & Moreno, 2010). Various inequality indices and alternative econometric strategies (cross-section, panel data and spatial econometrics) have been used in the process.

Initially, this analysis will use the mutual information index (MII) to compute the concentration of regional activity in the European Union. This measure is an entropy measure (i.e. a relative specialization measure) related to the Theil index. However, the MII takes into account the presence of isolation within the specialization distribution and considers a reduction in uncertainty due to a knowledge of others within the formulae. For this reason, the fact that each economic region knows the specialization levels of their European regional counterparts is incorporated within the computation. In addition to this, some

European regions become somewhat isolated as they show a specialization very unlike the general pattern of distribution. In fact this isolation has an impact on the evenness and representativeness of the specialization distribution. This problem affects the widely used Entropy index, which fails to fulfil two ordinal axioms (Frankel & Volij, 2009), but this is partially overcome when computing with the MII. Frankel & Volij (2009), although examining ethnic segregation across districts and schools, state that ordinal axioms refer to bilateral comparisons and not to their specific functional representations. In other words, MII allows for a greater degree of comparability than the Entropy index.[4] The MII computes an Entropy measure by introducing the average entropy value into the concentration measurement, since each region j knows the overall European regional specialization pattern. It can be simply computed as shown in Equation (1):

$$MII_j = E(s_{ij}) - \sum_n s_i(E(s_i)) \tag{1}$$

where s_{ij} represents the share of employment in sector i in region j as part of the total employment of region j, where s_i is the average share of employment for each sector across all regions and $E(q)$ is the entropy measure $\left[E(q) = -\sum_k q_k \cdot \log(1/q_k)\right]$, with q being the measure of interest (s_{ij} and s_i respectively) and k its number of units.

Nevertheless, the MII distributional shape shows a high degree of sensitivity to minimal distributional changes and this could have consequences for the drawing of inferences. Thus two alternative relative inequality measures are computed to check the sensitivity of the results to the specialization measure selected. For this purpose we compute the dissimilarity index (Equation (2)) and the Krugman index, which is the relative mean deviation (Equation (3)) from a benchmark region l.

$$DS_j = \sum_i \left| s_{ij} - s_i \right| \tag{2}$$

$$K_{jl} = \sum_i \left| s_{i,j} - s_{i,l} \right| \tag{3}$$

Although our interest relies on a robustness check, we need enough statistical variation in the endogenous variable to allow us to draw the necessary inferences. Figure 2, first part, displays the overall disparities for the specialization measures considered. We observe that the indices present sufficient statistical variability, except the Entropy measure. Consequently, and as this measure is strongly related to the MII, we do not present our results based on that measure. Figure 2, second part, also shows that most of the variation occurs after the expansion of the EU in the mid-1990s and over the period 2002–2005.

Next, the estimation of kernel density functions allows us to examine the presence of isolated regions when describing regional relative sectorial specialization distributions. Estimates are based on calculations using Gaussian kernel functions, while the smoothing parameter value was determined in each case following Silverman (1986). In this regard, Figure 3 displays significant differences in the specialization distribution based on the index selected. As can be observed, the MII distribution is more jagged than those obtained with the other indices. In fact, the five extreme values detected in the MII distribution do not appear when

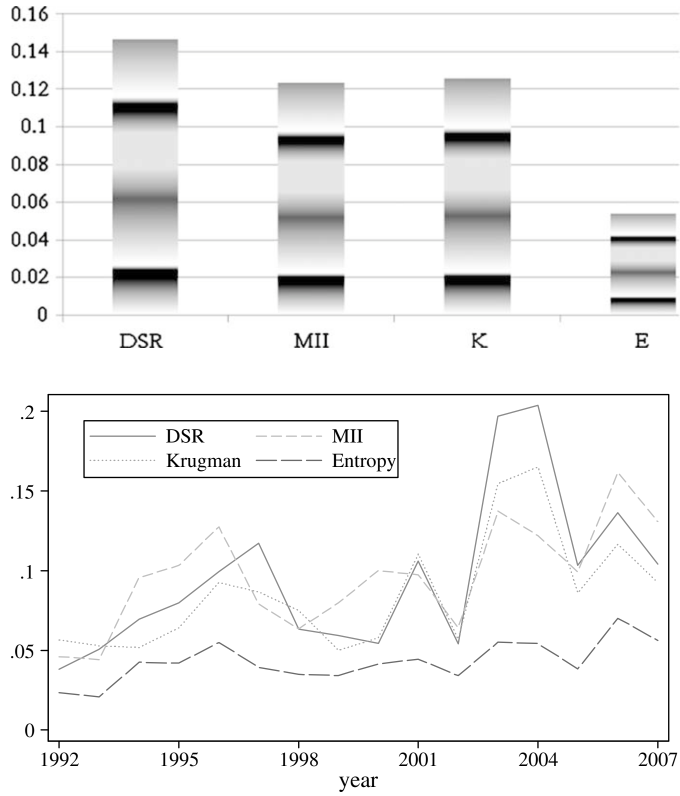

Figure 2. Disparities in several relative specialization indices.

Notes: Information regarding disparities accounts for all considered years. MII = Mutual Information Index, DS = dissimilarity index, E = general Entropy index and K = Krugman specialization index. We have computed the standard deviation of these measures. Below, we show the evolution in these indices on an annual basis.

applying the other inequality measures; yet all the distributions show a clear twin-peaked pattern at the end of the period under analysis. In fact, changes in the specific percentiles result in this scenario (Mora *et al.*, 2006).

Finally, a further key issue is that having categorized the European regions on the basis of their membership of CBR associations, we do not observe any statistically significant differences in the specialization levels of the indices computed (see Table 2). Furthermore, the same conclusion is reached when we divide the CBR associations on the basis of their age and the intensity of their cooperation programmes, but statistically significant differences were found regarding other covariates except for the proxies of market potential and patenting effort. In fact, CBR-associated regions show higher values in investment and earnings per employee but lower levels for population density, less skilled population in the regional labour market and proportion of agricultural employment. Finally, after disentangling CBR associations based either on intensity or age, we find statistically significant differences for most of the covariates considered.

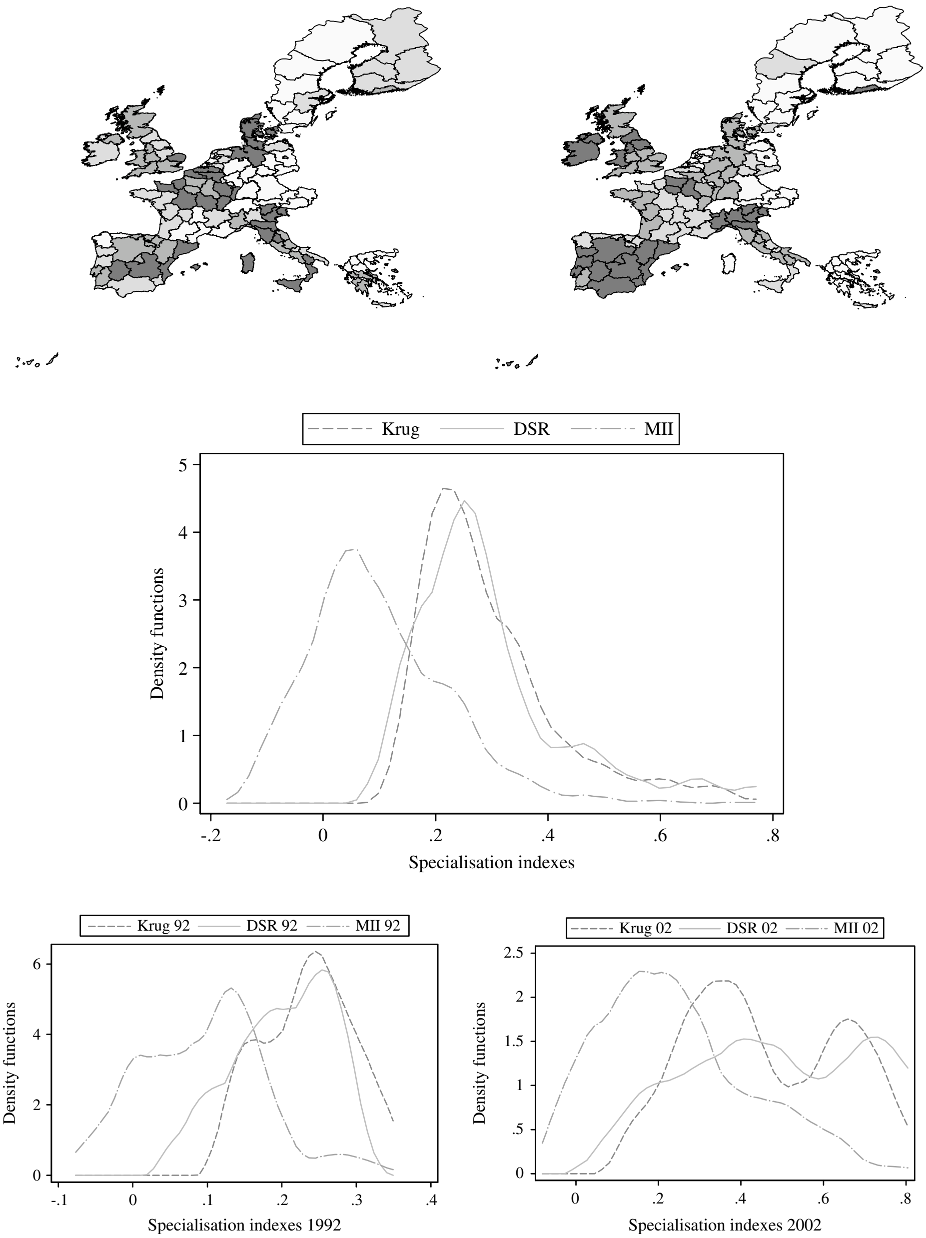

Figure 3. Regional specialization patterns in Europe.
Notes: Maps show MII spatial distribution in 1992 and 2000. Combined kernels in one plot refer to all years whilst the last row displays the three distributions in two specific years (1992 and 2002).

3.3. Econometric Strategy for Detecting Externalities

The panel data model that we initially specify explains specialization in region i in time t, $y_{i,t}$ through the consideration of a spatial lag model, as Equation (4a) shows. The period analysed is $t = 1992, \ldots, 2007$ and i represents each EU region.

Table 2. Average regional characteristics: statistical differences by CBRs

	Not associated in CBRs	Associated in CBRs	Non-intense CBRs	Intense CBRs	Non old CBRs	Old CBRs
Mutual information index	0.0974 (0.004)	0.0960 (0.004)	0.0956 (0.004)	0.0969 (0.008)	0.0960 (0.005)	0.0959 (0.007)
Dissimilarity index	0.3012 (0.004)	0.2983 (0.005)	0.2959 (0.005)	0.3038 (0.009)	0.2974 (0.006)	0.2998 (0.008)
Krugman specialization index	0.2964 (0.004)	0.2957 (0.004)	0.2935 (0.005)	0.3009 (0.008)	0.2952 (0.005)	0.2965 (0.007)
Investment levels	9.4310 (0.331)	12.9341 (0.510)***	11.2372 (0.527)	16.8934 (1.141)***	9.7454 (0.442)	18.4417 (1.102)***
Compensation per employee	21.3655 (0.277)	23.7565 (0.227)***	21.9386 (0.269)	27.9983 (0.300)***	21.8133 (0.282)	27.1129 (0.310)***
Market potential	1.5567 (0.014)	1.5333 (0.015)	1.56804 (0.015)	1.4523 (0.035)***	1.5104 (0.016)	1.5729 (0.029)**
Growth in the number of patents	0.1350 (0.018)	0.1283 (0.019)	0.1157 (0.020)	0.1579 (0.044)	0.1176 (0.022)	0.1468 (0.036)
% Agricultural sector	0.0589 (0.002)	0.0460 (0.001)***	0.0539 (0.002)	0.0275 (0.001)***	0.0571 (0.002)	0.0268 (0.001)***
Human capital	0.2654 (0.002)	0.25054 (0.003)***	0.2306 (0.004)	0.2972 (0.003)***	0.2304 (0.004)	0.2854 (0.003)***
Density of population	0.3393 (0.020)	0.2294 (0.012)***	0.2069 (0.012)	0.2821 (0.029)***	0.1838 (0.011)	0.3082 (0.026)***

Notes: We report average values and standard deviations in parentheses. We also report statistical differences compared to those regions not being associated in CBRs. ***, **, * denote significance at 1%, 5% and 10%, respectively.

The vector $X_{i,t}$ collects the regional macroeconomic variables that are useful for proxying the determinants of specialization, while $\varepsilon_{i,t}$ represents the error term. Thus Equation (4a) considers a spatial lag of the endogenous variable, i.e. the specialization average in the connected regions (a spatial autoregressive model) that can be estimated by using a maximum likelihood procedure. Note that β coefficients are not directly interpretable like in conventional regression models.

$$y_{i,t} = \rho W y_{i,t} + X_{i,t}\beta + \varepsilon_{i,t} \tag{4}$$

We denote the connectivity matrix by W, where a typical element w_{ij} (the degree of connectivity between regions i and j) has a value of 1 if regions i and j are connected and 0 otherwise. This implies that the specialization in each region is potentially affected by the specialization in their connected regions. In this paper we base connectivity on membership of CBR associations, i.e. $w_{ij} = 1$ when two regions belong to the same CBR association. At this juncture it should be noted that CBRs are made up of NUTS-3 regions. This means that, since our database takes into account different NUTS classifications for partially solving the modifiable administrative unit problem, we assign associations to its upper category. In a subsequent stage we compare our results when taking into consideration membership of CBRs with those obtained when using either a contiguity matrix ($w_{ij} = 1$ when two regions are contiguous in space) or a distance matrix (in which the elements are the inverse of physical distance from the capital city of each region, $w_{ij} = 1/d_{ij}$). Estimates using contiguity will constitute a benchmark for our parameter of interest (λ) when CBR information is taken into account. Note that all weight matrices were row-normalized.

One issue to be tackled is the selection of fixed effects versus random effects. Fixed-effect models are particularly appropriate when the regression analysis is limited to a precise set of individuals (such as regions), whereas random-effect models are a more appropriate specification when drawing a certain number of individuals from a larger population (Baltagi, 2001). We rely on estimates from the fixed-effect model because the Hausman test rejects its null hypothesis (with a value of 50.04, $p = 0.000$), and so the estimators obtained from the fixed-effect model are consistent. Time-fixed effects were statistically significant ($F = 98.21$; p-value $= 0.00$). We therefore address these effects into the specification (Equation (4b)), i.e. α_i represents regional fixed effects and η_t identifies time-fixed effects, while $u_{i,t}$ represents the error term.

$$y_{i,t} = \rho W y_{i,t} + X_{i,t}\beta + \alpha_i + \eta_t + u_{i,t} \tag{4b}$$

However, specialization does not present a concrete theoretical ground like convergence equations or Verdoorn's law equations in Fingleton & López-Bazo (2006), to be explicitly approached by means of a spatial lag model. For this reason, our selection should rely on spatial dependence test results. Consequently an alternative specification is made to assume the presence of spatial correlation in the error term (Equation (4c)), where ρ is now called the spatial autocorrelation coefficient. This can be interpreted as reflecting the regions' common reaction to shocks because of omitted variables that are spatially correlated (Anselin, 1988). According to Anselin *et al.* (2006), a spatial error specification does not require a theoretical model for a spatial or social interaction process, but, instead, is a special case of a non-spherical error covariance matrix.

$$\begin{aligned} y_{i,t} &= X_{i,t}\beta + \alpha_i + \eta_t + z_{i,t} \\ z_{i,t} &= \rho W z_{i,t} + \nu_{i,t} \end{aligned} \tag{4c}$$

We then performed Lagrange multiplier (LM) tests to ensure that this was the right specification—specifically, the test known as the Lagrange multiplier for spatial lags (LM-LAG) and its associated Robust LM-LAG, testing for the absence of substantive spatial autocorrelation, which would be due to the spatial correlation in the endogenous variable; and the test known as the Lagrange multiplier for spatial errors (LM-ERR), along with the associated robust LM-ERR, testing for the absence of residual spatial autocorrelation, which would be caused by not including a structure of spatial dependence in the error term.[5] When both types of spatial autocorrelation are present, we decide which is predominant, comparing the value of the tests in the two cases. Table 3 shows that the spatial error model was the best based on LM spatial test results.

Finally, specialization patterns might exhibit correlation to certain spatial lags of the independent variables. We factored these interactions into Equation (4c) by adding $\beta W \cdot X_{j,t}$. However, none of these complementary covariates showed statistical significance except for the spatial lagged coefficient associated with regional human capital proxy in a few specifications. In any case, the results hardly change after including this specific covariate.

Geographical information for the specialization indices can be summarized using a measure of spatial association such as Moran's I test of the regional distribution of specialization. Specifically, the presence of a spatial dependence process implies that the value of a variable at a geographical point is functionally related to the value of the same variable in other locations. In order to test for the presence of global spatial dependence in the variables used in our paper,

Table 3. Tests for spatial dependence in the specialization equations

Spatial matrices	Specialization indexes	LM-LAG	Robust LM-LAG	LM-ERR	Robust LM-ERR
CBRs	Mutual information index	157.47***	0.12	205.66***	50.31***
	Dissimilarity index	87.46***	0.02	287.28***	199.85***
	Krugman specialization index	72.80***	0.04	277.71***	204.95***
Contiguity	Mutual information index	1,220.32***	40.63***	1,179.84***	0.14
	Dissimilarity index	1,527.25***	7.59***	1,571.94***	52.28***
	Krugman specialization index	1,458.67***	10.32***	1,513.42***	65.07***
Distance	Mutual information index	6,473.01***	193.08***	6,483.74***	203.81***
	Dissimilarity index	14,430.48***	124.83***	14,533.96***	228.31***
	Krugman specialization index	13,290.11***	183.76***	13,624.15***	517.81***
High intensity CBRs	Mutual information index	106.88***	3.25*	776.92***	673.30***
	Dissimilarity index	43.11***	0.05	975.92***	932.85***
	Krugman specialization index	26.81***	0.02	925.18***	898.39***
Older CBRs	Mutual information index	56.41***	0.80	424.32***	368.71***
	Dissimilarity index	19.46***	0.01	625.16***	605.71***
	Krugman specialization index	14.24***	0.18	723.85***	709.79***

Notes: ***, **, * denote significance at 1%, 5% and 10%, respectively. Results were obtained by means of codes available at: http://www.rri.wvu.edu/lacombe/matlab.html.

the standardized Moran's I statistic (Moran, 1948) was employed. This can be defined as:

$$I = \frac{N}{S_0} \frac{\sum_{i}^{N} \sum_{j}^{N} w_{ij}(x_i - \bar{x}) \left(x_j - \bar{x}\right)}{\sum_{i=1}^{N} (x_i - \bar{x})^2} \tag{5}$$

where x_i and x_j are the observations for regions i and j of specialization; $\bar{x}$ is the average of the variable in the sample of regions; and w_{ij} is the i–j element of the row-standardized W matrix of weights. $S_0 = \sum \sum w_{ij}$ is a standardization factor corresponding to the sum of the weights. Because it equals the number of observations, N, in the case of a row-standardized W matrix, N/S_0 is equal to 1 in such a case. In Moran's test the null hypothesis is spatial independence. In our analysis we use three different matrices of geographical contacts (border region associations, contiguity and the inverse of physical distance).

For reasons of space, Table 4 only shows the presence of a positive spatial dependence process for alternative computed specialization measures in three specific years. This implies that the value of the variable at a geographical point is functionally related to the value of the same variable in other locations. Only as a robustness check, the presence of spatial autocorrelation is corroborated with the significant values obtained by means of alternative spatial statistics such as the *c*-statistic given by Geary (1954).

4. Contiguity Effects in European Regional Specialization

As we wish to account for spatial dependence in the panel data, we estimate the fixed-effect spatial error model given in Equation (4c). Spatial autocorrelation models of this type can be estimated by applying the maximum likelihood method of estimation developed by Elhorst (2003). Table 5 outlines the panel data estimations for our specification of interest when estimating the determinants of European regional specialization, including the spatial autocorrelation term and considering the alternative specialization measures and several spatial weight matrices. It should be stressed that greater explanatory power was observed when accounting for CBR associations. Thus we observe a positive impact from neighbouring regions, irrespective of the spatial weight matrix used in the error term being positive and statistically significant. This result is corroborated by

Table 4. Standardized Moran's I index for the selected specialization indices

		1992	1997	2002	2007
Mutual information index	Border assoc.	0.396 (0.00)	0.598 (0.00)	0.576 (0.00)	0.270 (0.00)
	Contiguity	0.504 (0.00)	0.418 (0.00)	0.323 (0.00)	0.448 (0.00)
	Distance	0.093 (0.00)	0.064 (0.00)	0.084 (0.00)	0.078 (0.00)
Dissimilarity index	Border assoc.	0.292 (0.09)	0.298 (0.00)	0.491 (0.00)	0.128 (0.18)
	Contiguity	0.523 (0.10)	0.460 (0.00)	0.436 (0.00)	0.469 (0.00)
	Distance	0.108 (0.00)	0.077 (0.00)	0.071 (0.00)	0.079 (0.00)
Krugman index	Border assoc.	0.501 (0.00)	0.183 (0.05)	0.436 (0.00)	0.215 (0.03)
	Contiguity	0.407 (0.00)	0.409 (0.00)	0.434 (0.00)	0.484 (0.00)
	Distance	0.067 (0.00)	0.079 (0.00)	0.059 (0.00)	0.083 (0.00)

Table 5. Spatial error model estimation results: alternative specialisation measures

	Mutual information index			Dissimilarity index			Krugman specialization index		
	CBRS	Contiguity	Inverse distance	CBRS	Contiguity	Inverse distance	CBRS	Contiguity	Inverse distance
Investment levels	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(−0.52)	(−1.09)	(−0.72)	(0.00)	(−0.79)	(0.13)	(0.11)	(−0.78)	(0.14)
Compensation per employee	0.008	0.001	−0.001	0.007	−0.003	0.000	0.009	−0.001	0.000
	(5.41)***	(0.96)	(−0.42)	(3.66)***	(−1.54)	(−0.20)	(5.86)***	(−0.54)	(0.28)
Squared compensation per employee	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(−3.84)***	(−0.79)	(0.05)	(−2.51)**	(1.62)	(0.15)	(−4.24)***	(0.71)	(−0.32)
GDPpc levels	−0.002	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(−1.91)*	(−1.14)	(−1.41)	(−0.62)	(−1.43)	(−1.31)	(−0.67)	(−1.75)*	(−1.04)
Squared GDPpc	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.37)	(0.90)	(1.71)*	(0.25)	(0.99)	(1.61)	(0.13)	(1.16)	(1.35)
Market potential	−0.120	0.021	−0.015	−0.044	−0.083	−0.095	−0.138	−0.059	−0.060
	(−1.86)*	(0.29)	(−0.23)	(−0.57)	(−1.04)	(−1.32)	(−2.10)**	(−0.86)	(−0.98)
Growth in the number of patents	−0.001	−0.005	−0.004	−0.004	0.000	0.004	−0.011	−0.004	0.001
	(−0.19)	(−1.38)	(−0.97)	(−0.87)	(−0.05)	(0.87)	(−2.58)***	(−1.20)	(0.34)
% Agricultural sector	1.030	0.332	0.167	1.433	0.343	0.360	1.223	0.281	0.275
	(7.17)***	(2.91)***	(1.28)	(8.35)***	(2.75)***	(2.57)**	(8.40)***	(2.61)***	(2.29)**
Human capital	0.150	−0.019	−0.027	−0.028	−0.083	−0.120	0.048	−0.046	−0.113
	(2.60)***	(−0.39)	(−0.51)	(−0.41)	(−1.56)	(−2.09)**	(0.82)	(−1.00)	(−2.31)**
Density of population	0.000	0.003	0.013	0.013	0.015	0.021	0.000	0.010	0.014
	(−0.02)	(0.34)	(1.42)	(0.99)	(1.75)*	(2.24)**	(0.02)	(1.32)	(1.68)*
Human capital*Adhesion95	0.396	−0.020	0.187	0.879	0.259	0.711	0.739	0.189	0.599
	(1.87)*	(−0.09)	(0.96)	(3.47)***	(1.12)	(3.42)***	(3.44)***	(0.95)	(3.36)***
Spatial autocorrelation	0.361	0.696	0.929	0.409	0.740	0.942	0.407	0.735	0.939
	(13.62)***	(47.36)***	(75.29)***	(16.41)***	(56.44)***	(93.29)***	(16.28)***	(55.27)***	(88.45)***
Fixed and time effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
$N \cdot T$	2,080	2,080	2,080	2,080	2,080	2,080	2,080	2,080	2,080
R^2	0.1134	0.0561	0.0346	0.0678	0.0100	0.0210	0.0975	0.0251	0.0259
Log-likelihood	1,605.87	2,085.26	1,968.01	1,224.57	1,868.75	1,831.64	1,568.95	2,178.12	2,149.57

Notes: Statistics are reported in parentheses. ***, **, * denote significance at 1%, 5% and 10%, respectively. Results were obtained through Matlab codes available at: http://www.regroningen.nl/elhorst/software.shtml. All results include fixed and time effects.

considering the inverse of physical distance between each region within the spatial lag parameter. In fact the closer the two regions are to each other physically, the greater the influence on their sectorial specialization pattern. Our evidence corroborates previous findings on this issue (Ezcurra *et al.*, 2006; Mora *et al.*, 2006; Mora & Moreno, 2010), although this previous research contributed by means of cross-sectional data or shorter panels.

The estimated values of the spatial autocorrelation coefficient are only strictly comparable to each other when binary matrices are considered (CBR and contiguity). The estimated impact using the contiguity matrix constitutes a benchmark for use in the CBR results. Autocorrelation coefficients, after taking into account CBR associations, range from 0.36 to 0.41, whereas the use of a contiguity matrix shows a greater impact through the error term (ranging from 0.70 to 0.74). Although both estimated values are extremely high, the difference between them is only 0.34 points. Consequently, European integration can be seen to have had a significant effect, although when only common institutional links between cross-national border regions are considered, the neighbouring impact is lower by 46 percentage points.

Finally, apart from neighbouring effects—and although beyond the scope of this paper—some control variables appeared to be statistically significant and are worth mentioning here. The impact of the control variables barely changes when considering alternative spatial matrices and specialization measures, although a greater number of statistically significant variables were observed when estimating regional specialization by means of the Krugman specialization index. It should be taken into account that using CBRs as a spatial weight matrix means that the covariates' impact might be picked up through the spatial autocorrelation coefficient due to the dissimilar characteristics of the regions that make up this kind of association. Firstly, agricultural specialization levels were found to be one of the most relevant factors when explaining regional specialization. Secondly, the higher the increase in human capital endowment recorded for those regions over the mid-1990s, the greater the degree of regional specialization. It should be remembered that this measure is proxied by the proportion of individuals in the region that have attained medium or tertiary levels of education. This confirms the idea that highly skilled labour pools induce regions to increase their level of specialization. Thirdly, regional agglomeration and size proxies do not show clear statistical significance irrespective of the specification considered.

Next we computed additional robustness checks. We looked at the extent to which the specialization levels of the sample regions are driven by the agricultural sector. To this end we checked the robustness of the results by excluding the

Table 6. Spatial error model estimation results without accounting for the agricultural sector

Spatial autocorrelation coefficient	Mutual information index	Dissimilarity index	Krugman specialization index
CBRs matrix	0.368 (14.00)***	0.383 (14.85)***	0.359 (13.51)***
Contiguity matrix	0.671 (43.17)***	0.666 (42.40)***	0.654 (40.63)***
Distance matrix	0.928 (74.16)***	0.925 (70.96)***	0.922 (68.05)***
Intense CBRs	0.712 (13.99)***	0.709 (13.79)***	0.678 (11.92)***
Older CBRs	0.678 (11.91)***	0.667 (11.34)***	0.667 (11.34)***

Notes: Statistics are reported in parentheses. ***, **, * denote significance at 1%, 5% and 10%, respectively. All regressions include fixed and time effects apart from the previous list of covariates.

Table 7. Disentangling CBRs associations based on intensity and longstanding

	High intensity CBRs			Older CBRs to 1990		
	Mutual information index	Dissimilarity index	Krugman index	Mutual information index	Dissimilarity index	Krugman index
Investment levels	0.000	0.000	0.000	0.000	0.000	0.000
	(−0.51)	(−0.32)	(−0.29)	(−0.10)	(0.33)	(0.25)
Compensation per employee	0.008	0.006	0.008	0.007	0.005	0.008
	(5.04)***	(3.02)***	(5.32)***	(4.72)***	(2.79)***	(5.06)***
Squared compensation per employee	0.000	0.000	0.000	0.000	0.000	0.000
	(−3.47)***	(−1.95)*	(−3.75)***	(−3.37)***	(−1.93)*	(−3.69)***
GDPpc levels	−0.003	−0.001	−0.001	−0.003	−0.002	−0.002
	(−2.47)**	(−0.90)	(−0.85)	(−2.51)**	(−1.21)	(−1.25)
Squared GDPpc	0.000	0.000	0.000	0.000	0.000	0.000
	(1.92)*	(0.59)	(0.44)	(2.00)**	(0.94)	(0.85)
Market potential	−0.097	0.005	−0.104	−0.092	−0.008	−0.113
	(−1.52)	(0.07)	(−1.59)	(−1.41)	(−0.10)	(−1.70)*
Growth in the number of patents	0.001	−0.004	−0.010	0.002	−0.003	−0.009
	(0.26)	(−0.66)	(−2.26)**	(0.35)	(−0.49)	(−2.03)**
% Agricultural sector	1.085	1.588	1.341	1.101	1.615	1.362
	(7.41)***	(8.95)***	(8.91)***	(7.44)***	(9.02)***	(9.01)***
Human capital	0.212	0.029	0.092	0.222	0.040	0.100
	(3.74)***	(0.42)	(1.58)	(3.86)***	(0.58)	(1.71)*
Density of population	− 0.002	0.013	0.001	−0.004	0.010	−0.001
	(−0.21)	(1.03)	(0.07)	(−0.32)	(0.78)	(−0.11)
Human capital*Adhesion95	0.363	0.945	0.810	0.394	0.975	0.885
	(1.67)*	(3.59)***	(3.63)***	(1.83)*	(3.75)***	(4.03)***
Spatial autocorrelation	0.713	0.736	0.721	0.663	0.707	0.707
	(14.05)***	(15.77)***	(14.62)***	(11.14)***	(13.65)***	(13.65)***
Fixed and time effects	YES	YES	YES	YES	YES	YES
$N{\cdot}T$	2,080	2,080	2,080	2,080	2,080	2,080
R^2	0.1149	0.0693	0.0980	0.1152	0.0698	0.0996
Log-likelihood	1,589.44	1,190.04	1,531.19	1,569.23	1,172.25	1,524.19

Notes: Statistics are reported in parentheses. ***, **, * denote significance at 1%, 5% and 10%, respectively. All regressions include fixed and time effects.

agricultural sector when computing the specialization measures. Table 6 shows that no significant differences are found regarding the autocorrelation coefficient either for the accounted matrix or the specialization index.

We also examined the nature of the CBR associations. Here we looked at two elements: the level of intensity within the CBR associations (low or high) and the age of their agreements (before or after 1990) following Perkmann (2003). Hence we constructed two more spatial matrices: a high intensity CBR matrix and one for long-standing CBR associations. Table 7 shows our results for all three specialization measures. Again, note that the spatial error model was the best specification. It can be observed that after considering both matrices the autocorrelation coefficient is statistically significant, showing a greater impact than when using the whole CBR associations. This will confirm the idea that linked cross-border regions have a greater influence on each other than border regions without an institutional link.

5. Conclusions

Besides the traditional factors previously addressed in the literature, this paper has also investigated the determinants of European regional specialization by focusing on the impact of neighbouring externalities. In addition, it has examined a further two specific issues: cross-national neighbouring effects and the sensitivity of results to the specialization measure chosen.

Our results indicate that neighbouring associated regions in Europe have an impact on specialization patterns. This is corroborated when both physical contiguity and spatial distance are considered. We also find that when only considering those contiguities in which an institutional agreement is present (i.e. CBR associations), the contiguity impact through the error term is lower by 46%. The same results are found when using alternative specialization measures. Nevertheless, once we divide the CBRs on the basis of the intensity of their relationship, we find that the impact of contiguity on specialization patterns is greater in high intensity CBRs and long-standing CBR associations. Obviously, our findings show one main caveat. The omitted variable problem might be present. Although we used non-contemporaneous data for the covariates considered, unobserved shocks might be correlated with accounted explanatory variables throughout the empirical analysis or with regional effects.

In the wider setting of the literature on territorial cooperation, our results seem to provide some indication that EU-15 CBR associations may have a quantitative impact on the regions involved. However, we cannot state categorically that CBRs are a determinant of convergence as regards the degree of regional specializations on both sides of the internal borders. Furthermore, as the high intensity matrix reflects virtually the entire impact of the CBRs, it might be the case that as the intensity of cooperation between the regions increases, so does the impact on their specialization.

Notes

1. We are indebted to Salvador Barrios for providing preliminary computations from the European Labour Force Survey. We expanded the data in order to cover the whole period based on average growth rates.

2. We use the common formula for market potential data for each region j: $MP_{j,t} = \sum_{j \neq i} GDP_{i,t} \Big/ d_{ji}$ in which GDP represents the level of Gross Domestic Product and d_{ji} denotes the distance between the capital cities of regions i and j.
3. We are grateful to Raffaele Paci and Stefano Usai from CRENOS for providing us with the number of patents at regional level. Although the use of patents as a proxy for innovation is not without criticism, we have adopted it because it is the most widely used proxy in the literature on innovation.
4. See Alonso-Villar & Del Río (2009) for an extension of its axiomatic properties to the context of location.
5. In this regard, see Villaverde and Maza (2008).

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