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Article

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The Impact of Structural Funds on Regional Growth: A Panel Data Spatial Analysis

The European Union is one of the most prosperous areas of the world. However, huge disparities remain among its member states and regions. Given the persistence of those large regional inequalities, it is pertinent to analyse the efficiency of structural funds. In light of the neoclassical theory, these funds should contribute to improving the economic efficiency among the poorest regions, promoting regional convergence. However, the new economic geography states that structural funds may also facilitate the geographic concentration of economic activities, thus perpetuating regional imbalances. This article measures the impact of structural funds on regional convergence using a spatial econometric approach applied to an extended sample of European regions across a long time interval. Based on data for 96 EU regions during the period 1995-2009, a Durbin model with panel data is estimated in order to capture the effects of spatial dependence in both the lagged dependent variable and the independent variables. The results confirm the existence of conditional convergence and the importance of neighbourhood and spillover effects but do not detect the existence of positive impacts from structural funds.

Although the European Union is one of the most prosperous areas of the world, huge disparities remain among its member states and regions. With the entry of new members in 2004, this disparity increased significantly. In this sense, the economic and social cohesion became a fundamental objective of the EU, implying mechanisms of solidarity between regions.

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Regional imbalances were mentioned in the Treaty of Rome, founding the European Economic Community in 1957. However, the first fund to finance explicitly regional cohesion policies began in 1975 with the creation of the European Regional Development Fund. Later, in 1993, the Cohesion Fund was created to finance investment in the field of environment and transport networks in countries with GNP per inhabitant of less than 90% of the EU average (Hooghe, 1996). Since then, the financial envelope for the structural funds has increased, representing approximately €350 billion in the Community Support Framework 2007-2013 and €336 billion for the programming period 2014-2020 (about 33% the overall EU budget).

These funds are designed to support the goal of convergence, benefiting mostly poorer states or regions. As an exception, a smaller proportion of the funds targets, among other things, projects focused on the goals of competitiveness and employment, regardless of the level of wealth of the beneficiary country. Finally, an even smaller proportion of funds is driven to cross-border strategies (Vesmas, 2009).

The role of structural funds is at the centre of the discussion on the effectiveness of the EU regional policy to attain the desired goals of growth, competitiveness, economic, social and (more recently) territorial cohesion. In

fact, structural funds are aimed at increasing the returns on investment so as to promote faster growth, especially in the periphery (Marzinotto, 2012). Nevertheless, the empirical results on this matter are far from being unanimous.¹

There are numerous studies analysing the convergence phenomenon among European regions, following different samples, technical approaches and, for diverse temporal sets, leading to different conclusions (Quah, 1996). The quality of data, particularly the categories of funds under study or whether they correspond to just commitments or real payments, affects the comparison among studies and increases the complexity of the subject. In addition, spillover effects highlighted in the new economic geography theory are not always properly treated, leading to biased results (see e.g. Dall'erba, 2005; Dall'erba and Le Gallo, 2008; Fingleton and López-Bazo, 2006).

Our work contributes to the deepening of current knowledge on the impact of structural funds for regional convergence within the European Union. In particular, the article seeks to address three questions: (i) Is there evidence of spatial dependence across European regions? (ii) How do spatial spillovers work, i.e. what kind of impact does a region's income have on nearby locations? (iii) How do structural funds operate, i.e. do they directly or indirectly impact a region's income level? In the latter, this may take place either through spatial spillovers from the funds received by neighbours (weighted spatial average of the funds) or due to the fact that funds affect nearby locations which, in turn, impact the development of a given region (weighted spatial average of income). To this purpose, we use a long series of data covering the period between 1995 and 2009 with structural funds actually spent (not just commitments) for a sample of 96 European regions. As stated by Elhorst (2003), panel data provide more information, increase the degrees of freedom and improve the quality of the estimation results. Knowing that regions interact with each other according to their degree of geographical proximity, our approach uses the techniques of spatial econometrics to model the spillover effects, using the estimator for panel data proposed by Elhorst (2003) and also used in Mohl and Hagen (2010).

Data and analytical framework

For the convergence analysis we focus on variables with increasing returns properties (like human capital and

¹ See Mohl and Hagen (2010) for a comprehensive empirical literature review about the impact of structural funds on economic growth.

technology) and on the role of the EU financial support. Our goal is to analyse the determinants of real per capita income growth. For that purpose, the following explanatory variables are considered (in logs): real per capita income, annual population growth rate, the investment share, innovation proxied by the number of patents per million inhabitants, human capital measured by the ratio of population aged 25-64 with tertiary education and (interpolated) real per capita structural funds.

The choice of control variables in regional convergence studies is highly conditioned by the availability of data. Dall'erba and Le Gallo (2008) use the labour share in the agricultural sector as a proxy for the industrial structure. The number of patents per million inhabitants is considered in many studies as a proxy for human capital. Fingleton and López-Bazo (2006) use transport costs and the average temperature to capture social and cultural effects. In our empirical estimation, we add the investment share, following Mohl and Hagen (2010). With the increasing mobility of labour, the endogeneity of the population variable may be an issue. However, European data point to a reduced population mobility. According to Dijkstra and Gakova (2008) and based on EU datasets, only 0.98% of the working population moved across regions to look for work in 2006.

Cross-section studies have been considered the most fruitful estimation procedure of regional convergence. However, those procedures ignore the fact that cross-regional data are normally affected by spatial dependence leading to potential multicollinearity, endogeneity and specification errors (Islam, 1998; Mankiw et al., 1992). We use the Moran's I index (Moran, 1950) to measure spatial autocorrelation, given by

$$I = \frac{n}{\sum_{i=1}^n \sum_{j=1}^n w_{i,j}} \frac{\sum_{i=1}^n \sum_{j=1}^n w_{i,j} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n x_{i,t} x_{j,t}} \quad (1)$$

where n represents the number of observations, x_i is the value of the variable analysed in region i , \bar{x} is the average value for the variable and $w_{i,j}$ is the proximity criterion between locations i and j . The set of weights, $w_{i,j}$ form the weight matrix W , which can be constructed with different proximity criteria. As a benchmark, we use the normalised first order contiguity spatial weights matrix. Formally, we define our weight matrix as follows:

$$W = \begin{cases} w_{i,j} = 0 & \text{if } i = j \\ w_{i,j} = 1 & \text{if } d_{i,j} = 0 \\ w_{i,j} = 0 & \text{if } d_{i,j} > 0 \end{cases}$$

The Moran scatterplot is associated with Moran's I statistic in order to detect the existence of spatial clusters, outliers and non-stationarity. In general terms, a given x -variable is standardised and plotted on the horizontal axis and the weighted average of x for the neighbours is on the vertical axis. The scatterplot contains four quadrants: one represents clusters of high-high values (top-right quadrant); another shows low-low values (bottom-left); and the remaining illustrate low-high and high-low values (top-left and bottom-right, respectively; Florax and Nijkamp, 2003).

Note that the Moran's I index is a general index that determines the overall trend for similar units to aggregate or not with each other within a population. But it tells us nothing about the specific location and distribution of these potential clusters. To overcome this weakness, Anselin (1995) proposed a local version of Moran's I statistic, which takes, for each region i , the following expression:

$$I_i = \frac{x_i}{\sum_i x_i^2} \sum_j w_{i,j} x_j$$

The observations x are centred on the average. Positive (negative) values of I_i indicate a concentration of similar (dissimilar) regions. A randomisation approach is used to generate a spatially random reference distribution to assess statistical significance (we use 999 permutations). Combining the information contained in the Moran scatter plot with the levels of significance of the local Moran index, we obtain the Moran significance map or LISA (Local Indicator of Spatial Association) cluster map in which only regions with significant LISA appear, with a specific colour for each quadrant localisation (Anselin et al., 2006).

Concerning the econometric estimation, the presence of spatial dependence refutes the independence of observations. In this sense, the validity of OLS estimators is undermined. Treatment of spatial autocorrelation can be accomplished in two ways: with a spatial lag in the dependent or independent variables (spatial lag model) or through the inclusion of autocorrelation in the disturbance term in which the spatial dependence is captured in the error term due to omitted variables or deficient functional form (spatial error model).² A third model (Anselin, 1988) is known as the spatial Durbin model and includes a spatial lag of both the lagged dependent variable and the explanatory variables.

The panel data approach is more adequate than cross-sectional analyses, allowing for individual and time effects

² For a comprehensive review about spatial econometrics, see for instance Anselin (1988), Le Gallo (2002) and LeSage (2008).

Table 1
Moran's I statistic, 1995-2009

Variables (in logs)	Moran's I	Marginal probability
Real per capita income	0.4880	0.0000
Investment share	0.8115	0.0000
Population growth	0.3270	0.0000
Human capital	0.0548	0.3590
Patents ratio	0.7870	0.0000
Real per capita funds	0.7192	0.0000

Sources: Authors' calculation.

as a way to control for unobserved heterogeneities across regions. Additionally, it makes it possible to integrate the process of convergence occurring over several consecutive time intervals.³ The extension of spatial analysis into a dynamic version of panel data occurred first in the early 2000s (Elhorst, 2003).

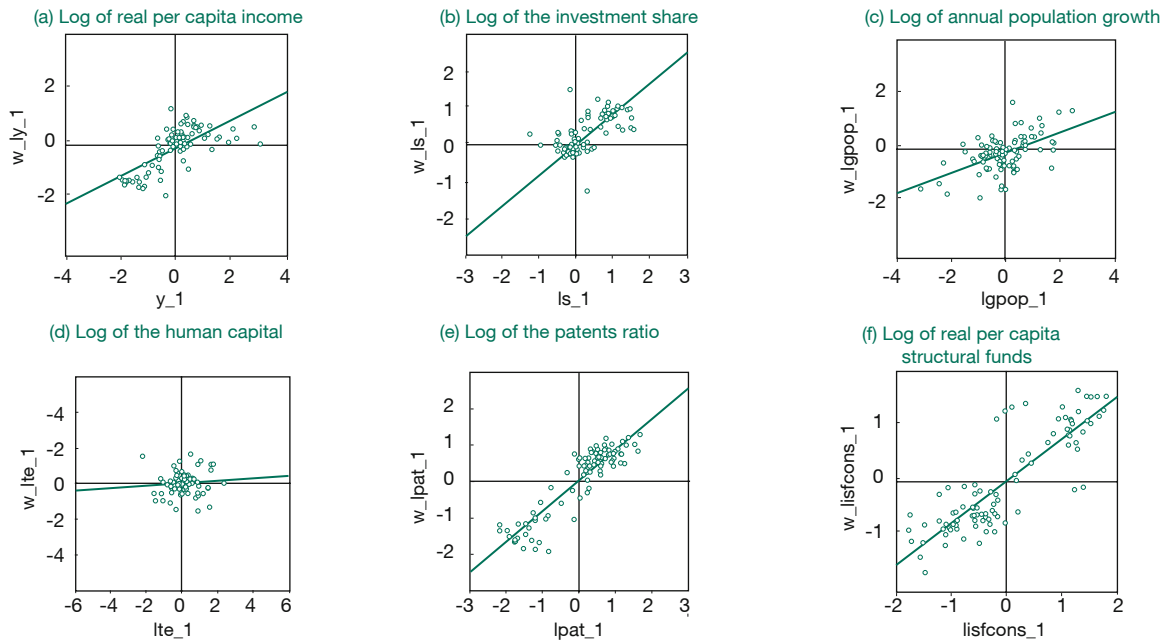
Agglomeration measurements

Table 1 displays the Moran's I statistic for the average values of our explanatory variables in the period 1995-2009. The Moran's I statistics for the main variables reveal positive and significant spatial correlation within the data except for the case of human capital. Figure 1 displays the Moran scatterplot for the average values of the variables. The predominance of regions in the top-right and bottom-left quadrants means positive spatial autocorrelation. With the exception of human capital (graph d), the Moran scatterplots confirm the pattern of positive autocorrelation for the remaining variables, with most regions falling between the high-high and low-low quadrants.

Figure 2 compares the quantile maps with the LISA cluster map for income per capita. Relative to per capita income, the quantile map clearly differentiates the north (richest regions) from the south (poorest regions). With the exception of the eastern regions of Germany, the decreasing gradient is clearly observed from east to west and from north to south. The LISA cluster map points to two large clumps of poor regions with strong spatial dependence, corresponding to the Iberian Peninsula (except the regions of Madrid, Catalonia and the Basque Country) and Greece. Interestingly, the high-high standard is not dominant, except for a few small spots in the UK and central Europe (East of England, Vlaams Gewest, Rheinland-Pfalz and Champagne-Ardenne).

³ For the advantages of panel data methods over cross-section studies, see Billmeier and Nannicini (2007), Islam (2003), Mankiw et al. (1992), Temple (1999).

Figure 1
Moran scatterplots



Sources: Authors' illustration.

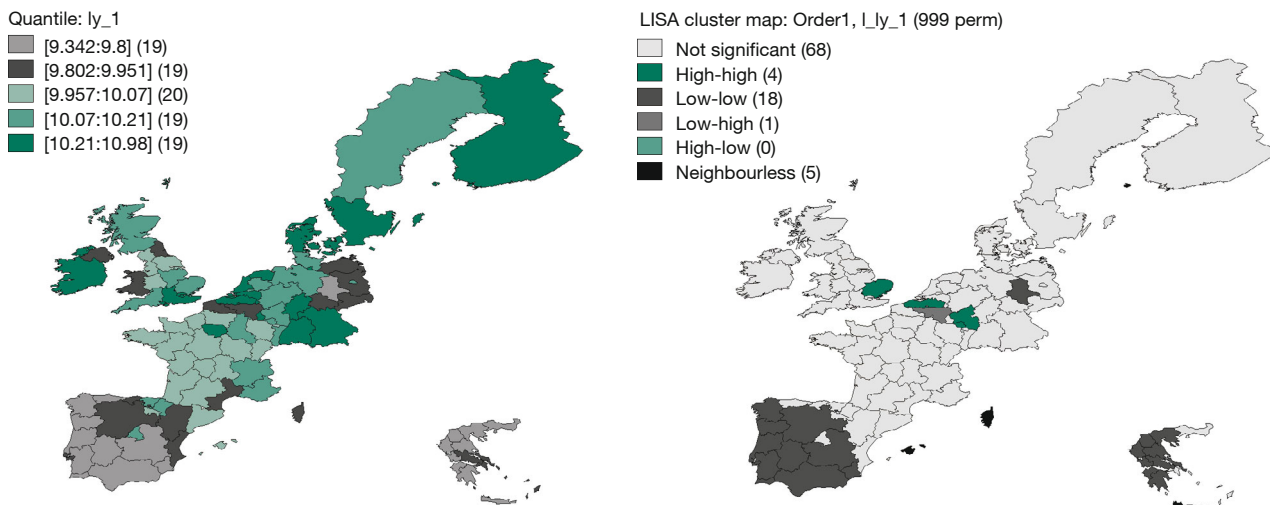
The exploratory spatial analysis with panel data

The present article estimates a model of conditional convergence at the regional level within 96 regions of the EU for the period 1995-2009. A non-spatial version of this model takes the following form:

$$g_{y_{i,t}} = c_0 + c_1 \ln(y_{i,t-1}) + c_2 \ln(gpop_{i,t-1}) + c_3 \ln(s_{i,t-1}) + c_4 \ln(pat_{i,t-1}) + c_5 \ln(hc_{i,t-1}) + c_6 \ln(sf_{i,t-1}) + \alpha_i + \delta_t + u_{i,t} \quad (2)$$

The subscript i refers to the 96 regions (n observations) and t is the time index. Region and time specific fixed ef-

Figure 2
Quantile and LISA cluster maps for real per capita GDP (1995-2009 average)



Source: Authors' illustration.

fects are represented respectively by α_i and δ_t , and $u_{i,t}$ is the independent and identically distributed error term. The dependent variable is the growth of real per capita income, $gy_{i,t}$. The (lagged) right-hand side variables are the following: $(y_{i,t-1})$, real per capita income; $\ln(gpop_{i,t-1})$, annual population growth rate; $\ln(s_{i,t-1})$, the investment share; $\ln(pat_{i,t-1})$, innovation proxied by the number of patents per million inhabitants; $\ln(hc_{i,t-1})$, human capital measured by the ratio of population aged 25-64 with tertiary education; and $\ln(sf_{i,t-1})$, real per capita structural funds.⁴ We opt for the fixed effects specification, based on the results from the Hausman's test (9863.98, p-value = 0.0000), indicating that the random effect model must be rejected in favour of the fixed effects model. Moreover, we follow Elhorst (2003), who considers the fixed effects model to be more appropriated with adjacent spatial units.

Table 2 confronts the pooled OLS estimation with the three versions of the fixed effects for the spatial model. We performed a likelihood ratio (LR) test in order to investigate successively the joint significance of spatial, time and both time and spatial fixed effects. Concerning the spatial fixed effects (model 2), we reject the null hypothesis of its non-significance (LR = 310.30 and $p < 0.01$). The same occurs with the joint significance of the temporal fixed effects (model 3: LR = 505.58 and $p < 0.01$). The joint significance of both time and fixed effects (model 4) cannot be rejected, either against the pooled OLS estimation or against the time fixed effects. As such, the extension of the model with spatial and time-period fixed effects is fully justified (model 4).

Table 2 reports the results of the Lagrange multiplier (LM) tests to determine the type of spatial dependence and the most appropriate model. We use both the classic LM tests (Anselin, 1988) and the robust LM tests described in Elhorst (2003). According to the former, and focusing our attention on the spatial and time period fixed effects model (model 4), both the null hypothesis of no spatially lagged dependent variable and no spatially autocorrelated error term are rejected. However, the robust LM test only rejects the null hypothesis of no spatially autocorrelated error term ($p < 0.05$), whereas the absence of a spatially lagged dependent variable cannot be rejected ($p = 0.2290$). Summing up, the outcomes point to the spatial error specification with spatial and time period fixed effects as the most appropriate model.

4 Since some values are null, to avoid losing observations we add 1 to the funds before computing the logarithm. Structural funds as a percentage of GDP was alternatively used and similar results were obtained.

Table 2
Estimation results and spatial dependence tests

	Pooled OLS	Spatial fixed effects	Time-period fixed effects	Spatial and time-period fixed effects
	(1)	(2)	(3)	(4)
Intercept	0.2845 (0.0001)			
$\ln(y_{i,t-1})$	-0.0284 (0.0000)	-0.2108 (0.0000)	-0.0091 (0.0685)	-0.1998 (0.0000)
$\ln(s_{i,t-1})$	-0.0118 (0.0018)	-0.0070 (0.2228)	-0.0137 (0.0000)	-0.0204 (0.0000)
$\ln(gpop_{i,t-1})$	-0.0151 (0.1661)	-0.0656 (0.0008)	0.0012 (0.8994)	-0.0521 (0.0021)
$\ln(pat_{i,t-1})$	0.0002 (0.8932)	0.0160 (0.0000)	0.0010 (0.3700)	0.0060 (0.0106)
$\ln(hc_{i,t-1})$	0.0035 (0.1983)	0.0113 (0.3968)	0.0039 (0.0875)	0.0529 (0.0000)
$\ln(sf_{i,t-1})$	-0.0030 (0.0178)	0.0008 (0.5823)	0.0033 (0.0096)	0.0006 (0.6681)
LogL	2325.8	2481.0	2578.6	2710.7
LM spatial lag	718.93 (0.0000)	594.5758 (0.0000)	134.4963 (0.0000)	128.9277 (0.0000)
Robust LM spatial lag	70.4460 (0.0000)	9.7587 (0.0000)	3.2117 (0.0730)	1.4448 (0.2290)
LM spatial error	675.93 (0.0000)	611.0528 (0.0000)	131.7804 (0.0000)	133.3301 (0.0000)
Robust LM spatial error	274.415 (0.0000)	262.357 (0.0000)	0.4958 (0.4810)	5.8471 (0.0160)
R ²	0.0346	0.2108	0.0208	0.1556

Note: p-values in parentheses.

Source: Authors' estimation.

Regarding the fact that some explanatory variables are spatially autocorrelated, we must consider another extension of our model. A full model with space and temporal fixed effects, and interaction effects, known as the spatial Durbin model, takes the specific form as in equation (3):

$$gy_{i,t} = \rho Wgy_{i,t} + c_1 \ln(y_{i,t-1}) + c_2 \ln(gpop_{i,t-1}) + c_3 \ln(s_{i,t-1}) + c_4 \ln(pat_{i,t-1}) + c_5 \ln(hc_{i,t-1}) + c_6 \ln(sf_{i,t-1}) + \gamma_1 W \ln(y_{i,t-1}) + \gamma_2 W \ln(gpop_{i,t-1}) + \gamma_3 W \ln(s_{i,t-1}) + \gamma_4 W \ln(pat_{i,t-1}) + \gamma_5 W \ln(hc_{i,t-1}) + \gamma_6 W \ln(sf_{i,t-1}) \alpha_i + \delta_t + \varepsilon_{i,t} \quad (3)$$

In order to control for the endogeneity problem created by the inclusion of the spatially lagged dependent variable, our results are based on a fixed effects spatial lag setup using the maximum likelihood (ML) estimator proposed by Elhorst (2014). The results of the spatial autoregressive and the Durbin model estimations are shown in

Table 3
Estimation results: Spatial error (1) and Durbin model (2)

	(1)		(2)		
		Coef- ficient	Direct effects	Indirect effects	Total effects
Wy		0.3943 (0.0000)			
$\ln(y_{i,t-1})$	-0.1943 (0.0000)	-0.1931 (0.0000)	-0.2013 (0.0000)	-0.1357 (0.0000)	-0.3370 (0.0000)
$\ln(s_{i,t-1})$	-0.0154 (0.0022)	-0.0153 (0.0022)	-0.0159 (0.0024)	-0.0107 (0.0049)	-0.0266 (0.0027)
$\ln(gpop_{i,t-1})$	-0.0790 (0.0000)	-0.0850 (0.0000)	-0.0899 (0.0000)	-0.0607 (0.0001)	-0.1507 (0.0000)
$\ln(pat_{i,t-1})$	0.0045 (0.0523)	0.0050 (0.0311)	0.0051 (0.0392)	0.0035 (0.0497)	0.0086 (0.0413)
$\ln(hc_{i,t-1})$	0.0516 (0.0000)	0.0518 (0.0000)	0.0534 (0.0000)	0.0360 (0.0006)	0.0894 (0.0001)
$\ln(sf_{i,t-1})$	0.0008 (0.6140)	0.0011 (0.4707)	0.0012 (0.4541)	0.0008 (0.4634)	0.0021 (0.4563)
$W * \ln(y_{i,t-1})$		0.0615 (0.0869)			
$W * \ln(s_{i,t-1})$		-0.0130 (0.1919)			
$W * \ln(gpop_{i,t-1})$		0.1391 (0.0000)			
$W * \ln(pat_{i,t-1})$		0.0068 (0.2194)			
$W * \ln(hc_{i,t-1})$		-0.0171 (0.5188)			
$W * \ln(sf_{i,t-1})$		0.0002 (0.9440)			
λ	0.4222 (0.0000)				
LogL	2768.0061	2776.96			
LR Test for Durbin model		24.92 (0.0003)			
R ²	0.1562	0.1790			

Note: p-values in parentheses.

Source: Authors' estimation.

Table 3.⁵ In order to estimate the statistical contribution of the Durbin model, we proceeded with an LR test with the null hypothesis, H₀, according to which the spatial Durbin model can be simplified to the spatial error model (Anselin, 1988). According to the result ($p = 0.0065$), we accept the Durbin against the spatial error model.

5 All calculations are based on Elhorst (2003). We use the author Toolbox functions (Matlab version) available at <http://www.regroningen.nl/elhorst/software.shtml>.

Many studies on regional convergence have neglected the effects of spillover and spatial correlation. Spatial correlation affects the independence of observations generating potential effects of bias in OLS estimators. The Durbin model, which proved to be the most appropriate, confirms the existence of spatial autocorrelation, with a highly significant coefficient of 0.39 in line with Mohl and Hagen (2010) and Dall'erba and Le Gallo (2008). Accordingly, the presence of significant spatial dependence reduces the coefficients compared to the OLS estimation. This means that an increase of 1% on the average per capita GDP of the neighbourhood of a given region will be reflected in an increase of 0.39% in the per capita GDP of this region.

The remaining variables, with the exception of the structural funds, show significant impacts with the expected sign, in line with most of the literature, thus confirming the presence of significant spatial effects (Dall'erba and Le Gallo, 2008; Mohl and Hagen, 2010). The negative sign of the lagged per capita GDP confirms the hypothesis of convergence of the poorest regions. The impact of population growth is also negative, reflecting the results generally found in the literature. The role of human capital and innovation is positive and statistically significant, though its value is reduced for the latter. The gross fixed capital formation impacts negatively on economic growth, although the effect is very small, a result also found in part by Mohl and Hagen (2010). This result confirms some crowding-out effects of public investment on private investment. Moreover, it also supports the new economic geography point of view, according to which the improvement of transport infrastructure in the poorest regions leads to an increased effect of agglomeration of economic activities in rich regions (Vickerman et al., 1999). Finally, the impact of structural funds is not significant. The absence of significant impacts of structural funds, confirmed by Dall'erba and Le Gallo (2008) and partly in Mohl and Hagen (2010), indicates their inability to counteract the agglomeration effects amplified by the decrease in transport costs.

Whereas the presence of spatial autocorrelation implies the existence of correlation between explanatory variables and the error term, thus producing inconsistent OLS estimators, we can analyse to what extent the estimated coefficients from the Durbin model confirm the bias effects. However, the comparison between the two models involves some caution in that the interpretation of the parameters in the Durbin model is more subtle, considering its direct and indirect effects (Anselin et al., 2006).

Contrary to spatial models, linear regression parameters have a direct interpretation as the partial derivative of the

dependent variable with respect to the explanatory variable. In models containing spatial correlation of the explanatory or dependent variables, the impact of a variable will not be equal among all regions.

Rewriting the Durbin model of equation (3) as

$$gy_{i,t} = (I - \rho W)^{-1} [c_1 \ln(y_{i,t-1}) + c_2 \ln(gpop_{i,t-1}) + c_3 \ln(s_{i,t-1}) + c_4 \ln(pat_{i,t-1}) + c_5 \ln(hc_{i,t-1}) + c_6 \ln(sf_{i,t-1}) + \gamma_1 W \ln(gy_{i,t}) + \gamma_2 W \ln(gpop_{i,t-1}) + \gamma_3 W \ln(s_{i,t-1}) + \gamma_4 W \ln(pat_{i,t-1}) + \gamma_5 W \ln(hc_{i,t-1}) + \gamma_6 W \ln(sf_{i,t-1})] + (I - \rho W)^{-1} [\alpha_i + \delta_i + \varepsilon_{i,t}] \quad (4)$$

LeSage and Pace (2008) suggest three measures of these impacts. The *total effect* sums the total impacts over the rows (or columns) of the matrix $(I - \rho W)^{-1}$, and then takes the average over all regions. The average of the diagonal elements of matrix $(I - \rho W)^{-1}$ provides the *direct effect*. Finally, the *indirect effect* is by definition the difference between the total effect and the direct effect. In short, the direct effect represents the impact of a change of the explanatory variable in region i on the dependent variable in the same region, including the corresponding feedback loops. According to LeSage and Pace (2008), the direct effect is similar in spirit to OLS coefficient interpretations. The indirect effect aggregates the impact of a change in the explanatory variable in all regions other than i in the dependent variable in region i .

As such, comparing the OLS model without spatial dependence with the direct effects of the spatial model, we found no significant differences regarding the effect of the lagged output and human capital. However, the OLS model overstates the negative impact of investment by more than 28% when compared to our spatial model. The same applies to the positive impact of innovation, overstated by nearly 18%. Finally, the negative impact of population growth is, instead, underestimated by 42%.

The estimated value for the lagged per capita GDP coefficient and its sign confirms the hypothesis of conditional beta convergence. The values are in line with those estimated in Mohl and Hagen (2010) and Dall'erba and Le Gallo (2008). With the estimated direct effects and assuming that all regions will converge at the same rate, we can calculate the convergence speed and half-life, respectively 22.48% and 3.1 years. However, it is important to relativise these results since there is, in the literature, still some ambiguity in terms of conclusive evidence regarding the notion of convergence in growth rates (see Nerlove (1997) for a comprehensive review).

Feedback effects of the Durbin model correspond to the difference between the direct effect and the value of the estimated parameters under study. In this case, we find

that these feedback effects, arising from the spatial correlation, are very small. For example, since the direct effect regarding innovation is 0.0051 and the respective coefficient is 0.0050, the feedback effect of innovation is only 0.0001.

Unlike feedback effects, indirect effects, not captured by the OLS model, are strong and significant. Except for structural funds, all other variables, including income, gross fixed capital formation, population growth, human capital and innovation have highly statistically significant indirect effects. Furthermore, the magnitude of these effects is also strong and similar across all variables, accounting for about 67%-68% of the respective direct effects. This means that a change in any of these variables has an impact not only on the income of this region but also on the income of its neighbourhood.

Conclusion

This paper aims to test the impact of structural funds on regional growth and the level of regional convergence across the EU. In light of the neoclassical theory, these funds should contribute to improving the economic efficiency among the poorest regions promoting regional convergence. However, the new economic geography states that structural funds, promoting the reduction of transportation costs, may also induce a geographic concentration of economic activities, thus perpetuating regional imbalances.

Considering that spillover effects are crucial in this respect, the use of spatial econometrics is fully justified in order to capture the neighbourhood effects and correct the bias of the OLS estimators. Our results confirm the existence of spatial autocorrelation in per capita income and in most of the explanatory variables. Relative to income and the distribution of funds, the exploratory spatial analysis confirms the concentration of structural funds in the poorest regions of the EU, in two main areas corresponding to the Iberian Peninsula and Greece. The econometric results of the Durbin model confirm the presence of spatial autocorrelation in income. Spatial autocorrelation causes important indirect effects that, in many cases, represent more than half of the direct effects. According to our results, the poorest regions tend to grow faster relative to the richer regions, confirming the existence of conditional convergence. Innovation and human capital positively affect economic growth while the effect of population growth is negative, in line with the literature. The impact of investment is significantly negative, although with a reduced magnitude. Concerning structural funds, we have not detected any significant

effects, i.e. the multiplier effects resulting from the construction of infrastructures have been cancelled by the agglomeration dynamic caused by the communication and transport improvements.

These results, which confirm the importance of neighbourhood and spillover effects, enhance the need for more studies to deepen the mechanisms of inter-regional connections that support these phenomena of spatial dependence as well as the main factors that generate externalities that may boost convergence. Furthermore, the non-significance of the impact of structural funds should not lead us to conclude that they are useless. Not supporting the poorest regions would likely have been worse. Thus, it is important to evaluate the type of investment, inferring whether there are substitution or complementarity relationships between public and (not funded) private investment. Our results suggest a crowding-out effect of structural funds. Moreover, it is important to consider that the absence or lack of other ingredients may have hindered the full use of all the potential of structural funds. More specifically, policies oriented towards education level improvement and promotion (and protection) of the innovative activity should be combined and coordinated with EU regional policy, in order to guarantee that financial transfers are efficiently and successfully allocated.

Our outcomes highlight the need to design policies intended to promote education and innovation in order to promote endogenous development dynamics on a regional scale. This is key to ensuring the success of regional policy, as announced by the Regional Development and Cohesion Policy beyond 2020. According to the 'thematic concentration', i.e. the repartition of resources by policy objectives, 65% to 85% of European Regional Development Fund and Cohesion Fund investments should be spent to promote "a smarter Europe" and "a greener Europe". Moreover, the need for simpler and decentralised procedures, requiring the involvement of stakeholders at different geographical levels should remain a top priority for the European Commission.

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