The impact of Structural Funds on regional growth: a Panel Data Spatial Analysis

Micaela Antunes[1], Miguel Viegas[2], Celeste Varum[3], Carlos Pinho[4]

Abstract

European Union (EU) is one of the prosperous areas of the world. However, huge disparities remain between its member states and regions. Given the persistence of those large regional inequalities, it is pertinent to analyze the efficiency of structural funds. In light of 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 cost, may also facilitate the geographic concentration of economic activities, thus perpetuating regional imbalances. Empirical results on this matter are far from being unanimous.

Our 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 interval time. Based on data of 96 EU regions during the period 1995-2009, we estimate a Durbin model with panel data, in order to capture the effects of spatial dependence in both the lagged dependent variable and the independent variables. Our results confirm the existence of conditional convergence and of the importance of neighbourhood and spillover effects but do not detect positive impacts of structural funds.

JEL classification: C12, R11, R12, O40

Key words: Structural funds, regional convergence, spatial panel econometrics, agglomeration effects

[1] CeBER, Faculty of Economics, University of Coimbra, Av. Dias da Silva, 165, 3004-512 Coimbra, PORTUGAL - mail: micaela@fe.uc.pt

[2] GOVCOPP, University of Aveiro (DEGEI), Campus Universitário de Santiago, 3810-193 Aveiro, PORTUGAL - mail: mlbv@ua.pt

[3] GOVCOPP, University of Aveiro (DEGEI), Campus Universitário de Santiago, 3810-193 Aveiro, PORTUGAL - mail: camorim@ua.pt

[4] GOVCOPP, University of Aveiro (DEGEI), Campus Universitário de Santiago, 3810-193 Aveiro, PORTUGAL - mail: cpinho@ua.pt

1. INTRODUCTION

Although the European Union (EU) is one of the prosperous areas of the world, huge disparities remain between 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 European Union, implying mechanisms of solidarity between richer and poorer regions.

Regional imbalances were enshrined in the Treaty of Rome, founding the European Economic Community in 1957. However, the first fund to finance explicitly regional cohesion policies only began in 1975 with the creation of the European Regional Development Fund (ERDF). Later, in 1993, the Cohesion Fund was created to finance investment in the field of environment and transport networks in countries whose GNP per inhabitant was 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 poor states or regions. As an exception, a smaller proportion of the funds have, as target, among others, 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.[5]

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 amounts or real payments affects the comparison between studies and increases the complexity of the subject. Finally spill-over effects highlighted in the new economic geography theory are not always properly treated, leading to biased results (see

[5] See (Mohl & Hagen, 2010) for a comprehensive empirical literature review about the impact of structural funds on economic growth.

(Dall'erba, 2005; Dall'Erba & Le Gallo, 2008; Fingleton & López-Bazo, 2006) among others).

Our work contributes to deepen the current knowledge on the impact of the Structural Funds for regional convergence within the European Union. In particular, the article seeks to address three questions: (i) if there is evidence of spatial dependence across European regions; (ii) how do spatial spillovers work, *i.e.*, the kind of impact that a regions' income has on nearby locations; (iii) how do Structural Funds operate, *i.e.*, if they impact directly on a region's development level or indirectly. In the latter case, this may take place either through spatial spillovers coming from the Funds received by neighbors (weighted spatial average of Funds) or by the fact that Funds affect nearby locations in terms of development levels 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) by a sample of 96 European regions. As stated by (Elhorst, 2003) panel data, providing more information, increase the degree of freedom and improve the quality of the estimation results. Whereas the regions interacting with each other according to their greater or lesser geographical proximity, our approach uses the techniques of spatial econometrics to model the spill-over effects, using the estimator for panel data proposed by (Elhorst, 2003) and also used in (Mohl & Hagen, 2010). The rest of the paper is organized as follows. The data and analytical framework are presented in section 2. Section 3 proceeds with the exploratory spatial data analysis and the discussion of results and section 4 concludes.

2. Data and analytical framework

For the growth analysis we focus on variables with increasing returns properties (like human capital and technology) and on the role of the EU financial support. Our goal is to analyze 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.[6]

The choice of control variables in regional convergence studies is highly conditioned by the availability of data. We found several solutions in the literature. (Dall'Erba & Le Gallo, 2008) uses the labor share in the agricultural sector as a proxy for the industrial structure and the unemployment rate, also used in (Rodríguez-Pose & Fratesi, 2004).

[6] We use real *per capita* Structural Funds. Structural Funds as a percentage of GDP was also used with similar result. Since some values are null, to avoid losing observations we add 1 to the Funds before computing the logarithm.

The number of patents per million inhabitants is also used in many studies. (Fingleton & 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 & Hagen, 2010). With the increasing mobility of labor, the endogeneity of the population variable may be an issue. However European data point to a reduced population mobility. According to (Dijkstra & Gakova, 2008) 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 that cross-regional data are normally affected by spatial dependence leading to potential multicollinearity, endogeneity and specification errors (Islam, 1998; Mankiw, Romer, & Weil, 1992). We use Moran index (Moran, 1950) to measure spatial autocorrelation:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{it}x_{jt}}$$

Where n, represents the number of observations, x_i, the value of variable in region i, $\bar{x}$, the average variable and $w_{i,j}$ 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 level we use the normalized first order contiguity spatial weights matrix. Formally we define our weight matrix as follows:

$$W(k) = \begin{cases} w_{ij}(k) = 0 \; if \; i = j \\ w_{ij}(k) = 1 \; if \; d_{ij} = 0 \\ w_{ij}(k) = 0 \; if \; d_{ij} > 0 \end{cases}$$

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

Note that the Moran index is a general index that determines, within a population, the overall trend for similar units to aggregate or not with each other. 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 centered on the average. Positive (negative) values of I_i indicate a concentration of similar (dissimilar) regions. A randomization 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 cluster map (according to the Geoda terminology) in which only regions with significant LISA (Local Indicator of Spatial Association) appear, with a specific color for each quadrant localization.

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 in econometric models can be accomplished in two ways: with spatial lag dependent or independent variables or through the inclusion of autocorrelation in the disturbance term, process by which the spatial dependence is captured in the error term due to omitted variables or deficient functional form.[7] The first model (with the lag dependent variable) is known as the spatial lag model, while the second as the spatial error model. A third model (Anselin, 1988a) labeled the spatial Durbin model includes a spatial lag of both the dependent variable and the explanatory variables.

The panel data approach reveals to be more adequate than cross-sectional analyses, allowing for individual and time effects 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.[8] The extension of spatial analysis to a dynamic version of panel data occurred only in the early 2000s (Elhorst, 2003). Thus, our work tries to identify and measure the effect of several regional growth factors from a panel data structure comprising 96 European regions for the 1995-2009' period using a spatial econometric approach as a means to embody eventual spill-over or proximity effects.

[7] For a comprehensive review about spatial econometric, see for instance, (Anselin, 1988b; Le Gallo, 2002; LeSage, 2008)

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

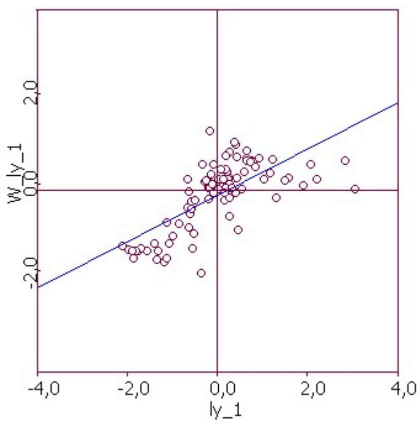
3. Empirical analysis

Agglomeration measurements

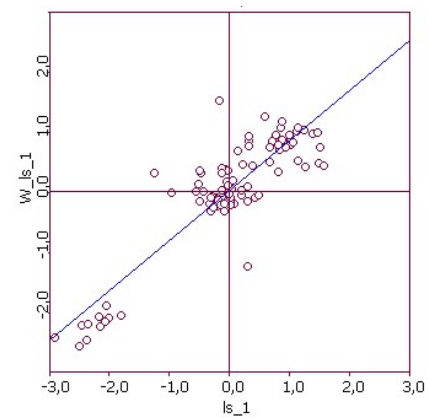
Table 1 displays the Moran's I statistic for the average values of our explanatory variables in the period 1995-2009. The Moran's I statistics for the main variables reveal positive and significant spatial correlation within the data except for the case of the human capital variable. Figure 1 displays the Moran scatterplot for the average value 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 remain variables, with most regions falling between the high-high and Low-Low quadrants.

Table 1: Moran's I statistic, 1995-2009.

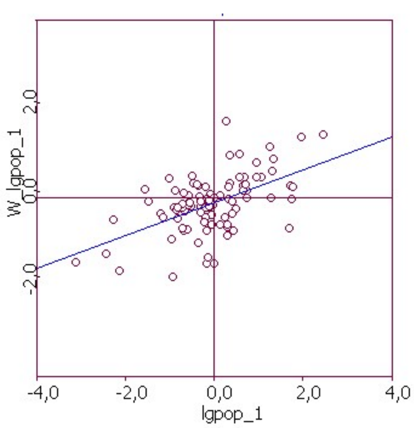
Variables (in logs)	Moran's I	Marginal Probability
Real per capita income	0.4880	0.0000
Investment share	0.8115	0.0000
Population growth	0.3270	0.0000
Human capital	0.0548	0.3590
Patents ratio	0.7870	0.0000
Real per capita Funds	0.7192	0.0000



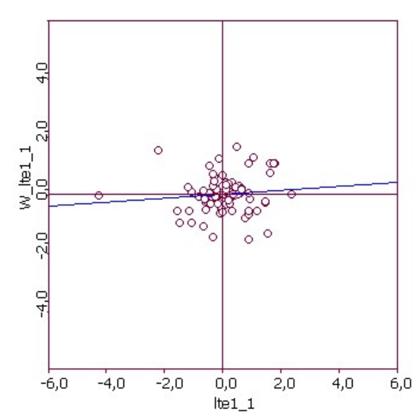
(a) Log of real per capita income



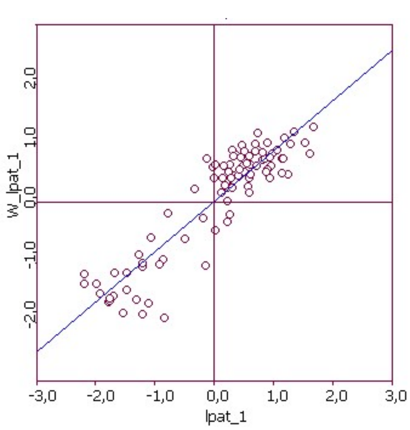
(b) Log of the investment share



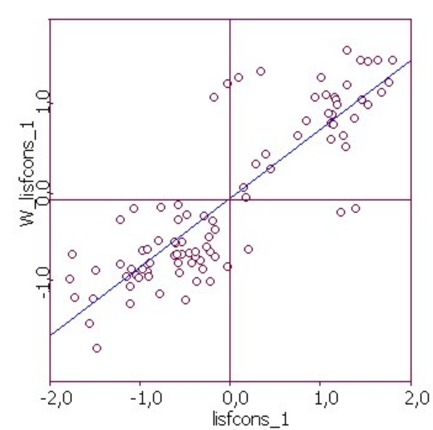
(c) Log of annual population growth



(d) Log of the human capital



(e) Log of the patents ratio



(f) Log of real per capita Structural Funds

Figure 1: Moran scatterplots.

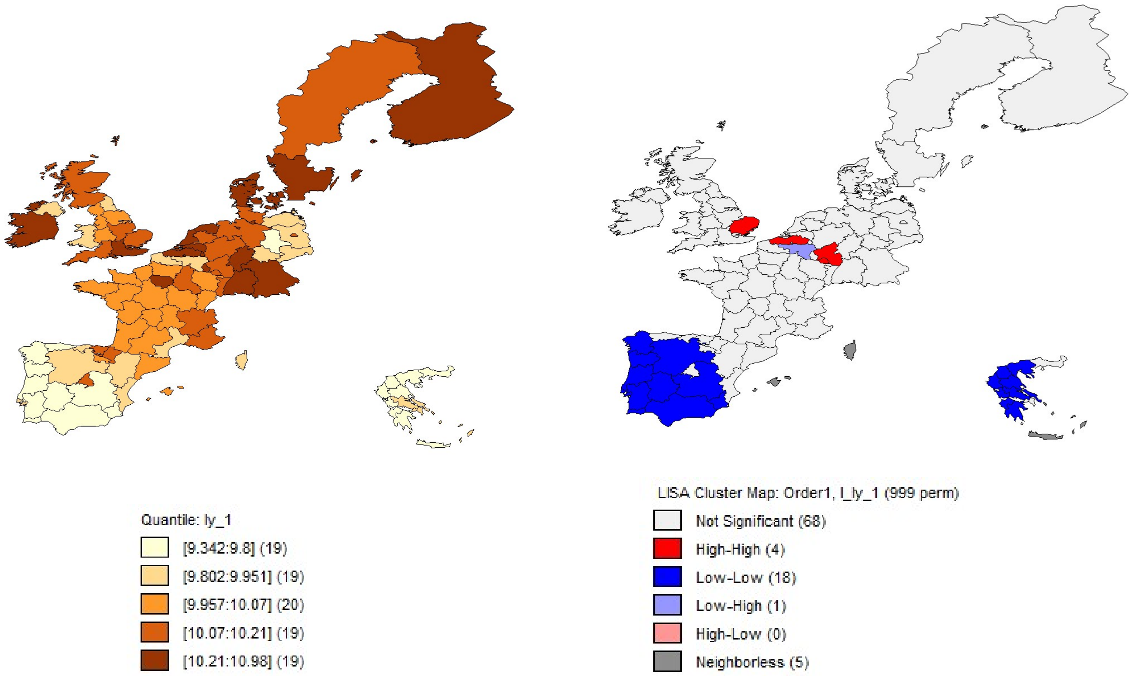


Figure 2: Quantile (left-hand side) and LISA cluster (right-hand side) maps for real per capita GDP (1995-2009 average).

Figure 2 compares the quantile maps with the LISA cluster map applied to income per capital. Relative to per capita income, the quantile map clearly differentiates the north with the richest from the south, with the poorest regions. With the exception of the eastern regions of Germany, the 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).

The exploratory spatial analysis with panel data

The present paper searches to estimate a model of conditional convergence at regional level within 96 regions of the European Union based on a set of explanatory variables. A non-spatial version of this model takes the following form:

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

Table 2: Estimation results and spatial dependence tests (p-values in parentheses).

	Pooled OLS (1)	Spatial fixed effects (2)	Time-period fixed effects (3)	Spatial and time-period fixed effects (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	27.4415 (0.0000)	26.2357 (0.0000)	0.4958 (0.4810)	5.8471 (0.0160)
R^2	0.0346	0.2108	0.0208	0.1556

The subscript i refer to the 96 regions (n observations) and t is the time index. State and time specific fixed effects are represented respectively by α_i and δ_t , and $u_{i,t}$ is the i.i.d. error term. The dependent variable is the growth of real per capita income ($gy_{i,t}$). The right-hand side variables are the following: $\ln(y_{i,t-1})$, 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. We prefer the fixed effects specification since we cannot consider the observation to be random draws from a large population. Besides, the result of the Hausman's test indicates that the random effect model must be rejected in favor or the fixed effects model.[9] Moreover, we follow (Elhorst, 2003) who consider that the fixed effects model is more appropriated with adjacent spatial units.

Table 2 confronts a first pooled OLS estimation with the three versions of the fixed effects model. We perform 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 effect, we reject the null hypothesis of non-significance (LR=310.30 with 96 df. and p<0.01). The same occurs with the joint significance of the temporal fixed effects (LR=505.58 with 15 df. and p<0.01). As for the join significance of both time and fixed effects, it cannot be rejected ether against the pooled OLS estimation ether against the time fixed effect. As such, the extension of the model with spatial and time-period fixed effects is fully justified.

Table 2 also reports the results of Lagrange multiplier (LM) tests to determine the type of spatial dependence and the most appropriate model to be applied. We use both the classic LM tests (Anselin, 1988b) and the robust LM-tests described in (Elhorst, 2003). According to the formers, and focusing our attention to the spatial and time-period fixed effects model (column 4), both the null hypothesis of no spatially lagged dependent variable and no spatially auto correlated error term must be rejected. However, the robust LM test only rejects the null hypothesis of no spatially autocorrelated error term (p<0.05), whereas the absence of spatially lagged dependent variable cannot be reject (p=0.2290). Summing up, the tests result points to the spatial error specification with spatial and time-period fixed effect as the most appropriate model.

Considering the fact that some independent variables are spatially autocorrelated, we must consider another extension of our equation. A full model with space and temporal fixed effects, endogenous interaction effect among the dependent variable and exogenous interaction effects among the dependent variables, known as the Spatial Durbin Model, takes the specific form:

$$g\,y_{i,t} = \rho W g y_{i,t} + c_1 \ln\left(y_{i,t-1}\right) + c_2 \ln(gpop_{i,t-1}) + c_3\, ln\left(s_{i,t-1}\right) + c_4 \ln(pat_{i,t-1}) + c_5 \ln(hc_{i,t-1})$$
$$+ c_6 \ln(sf_{i,t-1}) + \gamma_1 \mathrm{Wln}\left(y_{i,t-1}\right) + \gamma_2 \mathrm{Wln}(gpop_{i,t-1}) + \gamma_3 W\, ln\left(s_{i,t-1}\right) + \gamma_4 \mathrm{Wln}(pat_{i,t-1})$$
$$+ \gamma_5 \mathrm{Wln}(hc_{i,t-1}) + \gamma_6 \mathrm{Wln}(sf_{i,t-1}) + \alpha_i + \delta_t + \varepsilon_{i,t}$$
(2)

[9] The results (9863.98, 7 df and p= 0.0000) indicates that the null hypothesis (best fit of the random effect model) must be reject in favor of the fixed effects model.

Table 3: Estimation results: spatial error (1) and Durbin model (2) (p-values in parentheses).

	(1)	(2)			
		Coefficient	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			

In order to control for the endogeneity problem created by the inclusion of the spatially lagged dependent variable, ours 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 Durbin models estimations are shown in Table 3.[10] In order to estimate the statistical contribution of the Durbin model (results in column 2) we proceeded with a LR test testing the null hypothesis, H_0: $\gamma_i + \rho\beta_i = 0$, $\forall i$, according to which the spatial Durbin model can be simplified to the spatial error model (Anselin, 1988b). According to the result (p=0.0065), we must accept the Durbin against the spatial error model.

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 & Hagen, 2010) and (Dall'Erba & Le Gallo, 2008)). Accordingly, the presence of significant spatial dependence reduces the coefficients compared to the OLS estimation. This means that an increase of one percent on the average *per capita* GDP of the neighborhood of a given region will be reflected in an increase of 0.39% in the *per capita* GDP of this region.

For the remaining variables, and with the exception of the Structural Funds, all show significant impacts with the expected sign. 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 similarly to the results found in the literature. The role of innovation is positive and statistically significant, even though its value is reduced. The same happens with the human capital represented in our model by the level of education. The gross fixed capital formation impacts negatively on economic growth signal, although the effect being very small. Finally, the impact of structural funds is not significant. These results, aligned with most of literature, confirm the presence of significant spatial effects (Dall'Erba & Le Gallo, 2008; Mohl & Hagen, 2010). The negative impact of gross fixed capital formation, although quantitatively small, is also found in part by (Mohl & Hagen, 2010). This result confirms some crowding-out effect 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 poorest regions leads to an increased effect of agglomeration of economic activities in rich regions (Vickerman, Spiekermann, & Wegener, 1999). The absence of significant impacts of structural funds, confirmed by (Dall'Erba & Le Gallo, 2008) and partly in (Mohl & Hagen, 2010), indicates their inability to counteract the shadow effect of the richest regions caused by the decrease in transport costs.

Whereas the presence of spatial autocorrelation implies the existence of correlation between explanatory variables and error, producing inconsistent OLS estimators, we can

[10] All calculations are based on (Elhorst, 2003). We use the author Toolbox functions available at http://www.regroningen.nl/elhorst/software.shtml.

analyze to what extent the estimated values from the Durbin model confirm or not 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.

Thus, while in the OLS model each parameter represents the marginal effect of a change of the explanatory variable on the dependent variable, this is not the case in the spatial model. For comparison purposes, it is more appropriate to refer to the direct effect of the spatial model. 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 & Hagen, 2010) and (Dall'Erba & 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.[11] However, it is important to relativize these results since there is, in 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 regard 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 and innovation have statistically very significant indirect effects. Furthermore, the magnitude of these effects is also strong, accounting for about 67-68 percent of the respective direct effects (the magnitude is similar for each of the five variables). This means that a change in any of these variables has an impact not only in the income of this region but also in the income of its neighborhood.

[11] Growth rate of convergence: $\theta = -\ln(1+\beta)$ and half-life: $t = -\ln(2)/\ln(1+\beta)$

4. Conclusion

Our paper aims to test the impact of structural funds on regional growth and the level of regional convergence across the European Union. In light of 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 cost, 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 neighborhood effects and correct the bias of the OLS estimators. Our results confirm the existence of spatial autocorrelation in income (*per capita* GDP) 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 European Union, 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 the lagged dependent variable. 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 (education) positively affect economic growth while the effect of population growth is negative, in line with the literature. The impact of gross fixed capital formation is significantly negative, although with a reduced magnitude. Concerning structural funds, we haven't detected any significant effects, i.e. the multiplier effects resulting from the construction of the supported infrastructures have been canceled by the agglomeration dynamic caused by the communication and transport improvements.

These results, which confirm the importance of neighborhood 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. Furthermore, the non-significance of the impact of Structural Funds should not lead us to conclude about their uselessness. Not supporting the poorest regions would have been probably worse. Thus, it is important to evaluate the type of investment, inferring whether there is substitution or complementarity relationships between public and (no 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 levels improvement and promotion (and protection) of the innovative activity should be combined and coordinated with the EU Regional Policy, in order to guarantee that financial transfers are efficiently and successfully allocated.

Our conclusions regarding the need to design policies intended to promote education levels and innovation in order to ensure the success of Regional Policy find support in the announced 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 in the first two objectives: a Smarter Europe and a Greener Europe. Moreover, the simplification of procedures, the decentralization of the process and a greater role for agents at the local level remain as a top priority for the European Commission.

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