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Spatial analysis of regional placement services

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Abstract:

This study is motivated by evidence that even today differentials in regional placement have persisted in Spain. Also, the issue of decentralization is becoming important due to the transfer of Active Labour Market Policy to the Spanish Autonomous Communities. Many empirical labour market studies have ignored spatial effects. We are interested in comparing the spatial patterns of two types of vacancies: placement by PES and placement not by PES. We show evidence of global and local spatial autocorrelation using exploratory spatial-data analysis (ESDA) tools when we analyze the distribution of the vacancies filled due to the mediation of the PES for the period 2007-2008. This outcome is important if we ask where the market share of PES is really meaningful in terms of job vacancies filled. Also, the spatial distribution of placement by PES plays an important role in explaining the gap between provinces.

Keywords: public employment services, job vacancies, spatial dependence.

JEL Classification: J68, J60, C21, R12.

1. Introduction

The European employment strategy (EES) has provided the framework to strengthen the Public Employment Services (PES hereafter). The placement role of the PES has been emphasized since 1998. As a matter of fact, the guidelines for the period 2005-2008 insist on the role of the PES at local level in the labour market.

The use of PES is most often tackled by pointing to business cycle conditions or cooperation between public and private employment services. Authors like Thuy (2001) or De Koning (2007) point out that the deregulation of placement services is a natural consequence of the general trend in most EU countries. Our purpose is to examine the performance of the Public Employment Services operating in Spain during 2007 and 2008 once the transfer process of Active Labour Market Policy (ALMP) has been completed.

The literature related to the use of PES usually centres on the relationship between their use and the economic cycle. For instance, Osberg (1993) and Gregg et al. (1996), in a study of the public employment offices in Canada and the United Kingdom respectively, conclude that the use of the PES is counter cyclic. On the other hand, some papers are centred on the work developed by the PES at regional level, such as the following: Lundin et al., 2006; Ibourk et al., 2001; Ferro- Luzzi et al., 2003; Sheldon, 2003; Bruttel, 2005; Vassiliev et al., 2006; Joassart-Marcelli et al., 2006, among others.

Recently, Clinch and O' Neill (2009) underlined the importance of space in order to evaluate the development of policies that have meant a high degree of decentralization, consideration of the theoretical framework providing the Spatial Economy to carry out evaluations being fundamental.

The literature in Spanish research into the placement role of the PES does not consider space explicitly. Nevertheless, Jimeno (1993) indicates that in the labour market spatial dimension has a special role since employers and workers should be put into contact in one place and at a specific moment.

Besides, the process of transfer of the ALMP to the autonomous regions has taken place recently in Spain so that, with the exception of the País Vasco[1], among their powers all the autonomous regions are responsible for the main activity of the PES, that is, brokerage (rapid match between supply and demand).

In this paper spatial dimension is considered as a fundamental element at the moment to explain the regional differences in terms of placements. We analyze the spatial dependence, on the one hand, job vacancies registered in the PES and filled with PES job-seekers and on the other hand, the number of vacancies not registered with the PES and filled with non PES job-seekers of both categories in 2007 and 2008.

This paper develops as follow: the hypothesis of this research is summarised in section 2. Section 3 describes the data and methodology, while section 4 reports the empirical results. Finally in section 5, we summarize the findings.

[1] An agreement exists so that powers in an active labour market policy are transferred to the País Vasco from January 2010 onwards.

2. Hypothesis: PES and spatial dependence

The hypothesis of this research is that if the labour market of PES is integrated, we would expect to see very similar results amongst neighbouring regions, total placement by PES in region **i** at time **t** is likely to be correlated with placement by PES of the neighbouring regions. Why do we expect to find this? There are two reasons as to why spatial dependence may exist between regions in the case of PES labour market.

Firstly, the job-seekers register in the Data Bank of job-seekers has a similar professional profile independent of the Public employment services of Autonomous Communities.

Secondly, the Public Employment Services of Autonomous Communities are integrated in the National System of Employment, so all of them offer the same service. Furthermore, the process of decentralization of the ALMP has been completed in Spain.

In the Spanish context, there are not many studies on the PES from a regional perspective. Alujas (2007) has studied the labour mediation of the SPE in Spain at autonomous level before the introduction of the Information System of Public Employment Service (SISPE), although the role of space is not considered explicitly. López-Bazo et al. (2002) uses spatial techniques to analyze the distribution of unemployment in Spain from a regional outlook at two points in time, 1985 and 1997.

Karlsson et al. (2002) synthesize the reasons for which spatial perspective should be borne in mind at the moment of analyzing the labour market. Firstly, the labour market is not homogeneous as neoclassical theories proclaim. From a macroeconomic point of view, the segmentation of the labour market is associated with spatial segmentation. Secondly, different spatial patterns have been found in the distribution of unemployment in many countries. Finally, local labour market areas change over time, due to, for example, improvements in the infrastructure, or creation of new jobs and/or a different level of immigration. For example, in Denmark in 2007, the government established 4 well-defined "local labour market areas" that changed in 14 regions recognized administratively.

The analysis of the regional labour market cannot ignore the theoretical framework provided by Spatial Economy. Our intention here is to point out the need to analyze the spatial connectivity of provinces in a decentralization context. In this paper, the first aim is to analyze the spatial distribution of the vacancies filled for the period 2007-2008 in the Spanish provinces.

We show evidence of global and local spatial autocorrelation using exploratory spatial-data analysis (ESDA) tools in the case of the distribution of the vacancies filled due to the mediation of the PES. The second aim is to incorporate the spatial connectivity relationships in spatial regression models. Finally, we observe the existence of spatial heterogeneity and detect two different spatial regimes.

3. Data and Methodology.

a. Data

The first problem was the selection of the data and cross tabulating the filling type vacancy. The administrative data set available for this study is considerably new and not yet exploited. In the framework of the SISPE and relating to the placements, these statistics have been studied very little with the exception of the work on administrative statistics by Albert and Toharia (2007) that analyzes placement data in Andalucía. Although the data have some problems, in our opinion, they are at present the best administrative data for evaluating PES.

The mediation of PES in the vacancy filled should be defined strictly; henceforth, the vacancy register in PES is filled with PES job-seekers (placement by PES) or the vacancy is not registered with PES and is filled with non PES job-seekers (placement by non PES or placement by market). We consider these two single possibilities as does De Koning (1999). In 2007 these two categories accounted for approximately 75% of the total placements[2].

The job offers are registered with the PES, so PES provides job offers given to the Employment Offices. How does one gain access to job offers? The jobseeker, after registering, is included in the Data Bank of job seekers, and can become a candidate, if his or her professional profile matches any of the job offers given to the Employment Offices.

As happens in other European countries, employers in Spain have no legal obligation to register their job vacancies with the PES but they have to communicate if they fill a vacancy. This information is collected in the statistics mentioned above.

Our data pertain to 47 province employment offices that operated during the period January 2007 to December 2008 (i.e., 24 months).

Table 1. Descriptive statistics

Variable		Mean	Stand dev.	Minimum	Maximum
Placement by PES	2007	7,825	7,224.563	639	27,870
	2008	7,026.872	7,072.949	894	27,823
Placement not by PES	2007	259,871.5	362,228.8	21,192	1,888,661
	2008	226,087.3	304,408.3	19,667	1,551,641
Male Placement by PES	2007	3,503.34	3,178.889	372	13,022
	2008	3,011.234	2,791.095	499	13,199
Male Placement not by PES	2007	144,743.2	191,124.4	10,729	977,375
	2008	122,040.5	156,619.3	9,942	788,077
Female Placement by PES	2007	4,283.894	4,306.647	267	15,728
	2008	4,021.404	4,424.645	395	15,619
Female Placement not by PES	2007	113,859.5	169,614.7	9,451	881,701
	2008	104,046.8	149,272.4	9,196	763,564

b. Methodology

In recent years, the development of the New Economy Geography has strengthened the need to include the role of space in theoretical economic models and, from a empirical perspective, the need for specification and estimate econometric models where the spatial relationships are included explicitly. In the labour market literature, there are some papers where the importance of the regional disparities is analyzed and one of the main conclusions is that regional disparities are higher than national disparities (Overman and Puga, 2002). Moreover, the existence of regional labour markets implies two needs: on the one hand, to identify specific or fixed factors and on the other, to take into account the different reactions

[2] The placements are jobs to be occupied by a worker, and they are assigned to the province in which the workplace is situated. They are distinguished from placements of active demands and other placements.

from each region to global (national or international shocks). The regional answers would be different in their direction and intensity.

However, an isolated analysis of regional economies would be incomplete and unrealistic due to the existence of economic relations (spatial externalities) among neighbouring regions or provinces. Then, the regional economic growth could not be explained only by their own capacity but the influence of neighbouring regions has to be considered. Therefore, if spatial dependence exists, it should be incorporated explicitly into econometric models avoiding specification errors.

There are some papers in the labour market literature relating to this question such as Elhorst (2003) and Longhi and Nijkamp (2007), among others. In the Spanish case, the role of spatial relations is studied in some papers form a different point of view. Then, Dall'erba (2005) analyzes the economic convergence including spatial dependence; explicitly. López-Bazo et al. (2002) study the spatial distribution of unemployment and Mayor and López (2008) propose and apply a spatial shift-share model to decompose the employment variation into spatial and structural effects.

The concept of spatial autocorrelation (Cliff y Ord, 1973) has been the object of different definitions and, in a general sense, it implies the absence of independence among the observations, showing the existence of a functional relation between what happens in one province and in all of them. The existence of spatial autocorrelation can be expressed as follows:

$$\mathrm{Cov}\left(X_i,X_j\right)=E\left(X_i,X_j\right)-E\left(X_i\right)E\left(X_j\right) \tag{0.1}$$

One of the characteristics of spatial dependence is its multidirectionality, that is to say; each region could be related to the whole group of neighbouring regions. This implies estimating $N(N-1)/2$ which is not possible due to the needed sample size. The most habitual solutions consist of the definition of a spatial weight matrix.

The spatial weight matrices $\mathbf{W}$ are symmetric and squared $(N \times N)$ and their elements w_{ij} are non-negative and show the intensity of interdependence between the spatial units i and j.

$$W=\begin{bmatrix} 0 & w_{12} & . & w_{1N} \\ w_{21} & 0 & . & w_{2N} \\ . & . & . & . \\ w_{N1} & w_{N2} & . & 0 \end{bmatrix} \tag{0.2}$$

According to Anselin (1988) the spatial weight could be collected according to diverse options. A well known alternative is the Boolean matrix, based on the criterion of physical contiguity and initially proposed by Moran (1948) and Geary (1954). In this case, the spatial weight w_{ij}=1 if i and j are neighbouring provinces and w_{ij}=0 in another case, the elements of the main diagonal being null.

In order to allow an easy interpretation, the weights are standardised by rows. Then, the elements of the standardized matrix are obtained as $w_{ij}^d=w_{ij}\Big/\sum_j w_{ij}$. According to this fact, the spatial lag variable is interpreted as a weight average of the values in its neighbouring units.

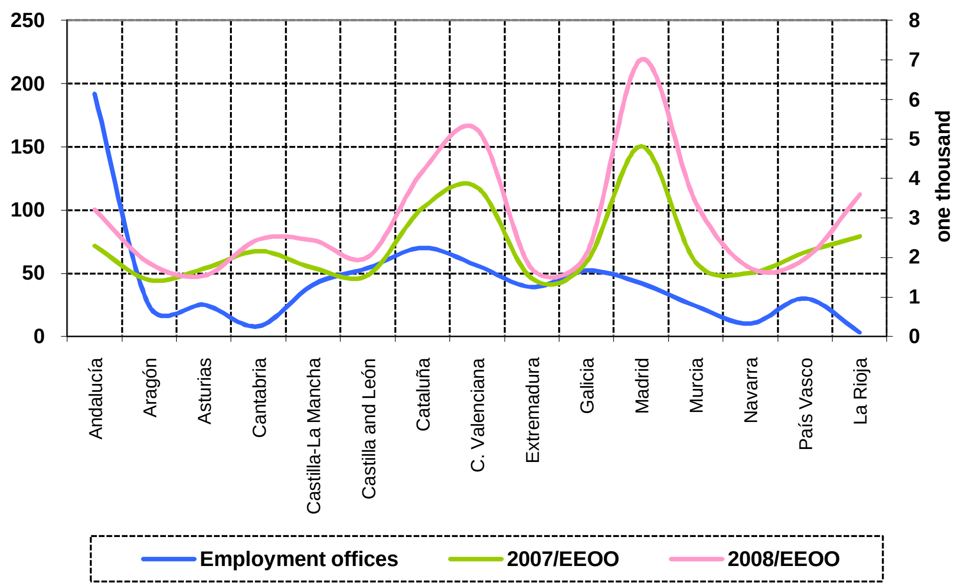
Another alternative to define the neighbouring regions is based on geographic distance. For example, two regions are considered as neighbouring if the distance between them is less than a criteria distance. In some cases the definition of weights is carried out according to the concept of "economic distance" as defined by Case et al. (1993) with $w_{jk} = 1/\left|X_j - X_k\right|$ X_j and X_k, being the per capita income or any economic variable.

The choice of the spatial weight matrix is a key step in spatial econometric modelling (Anselin et al. 2004) and nowadays there is no single method to select an appropriate specification for this matrix. Recently, Fernández et al. (2009) analyze different options to build the spatial weights and propose a new method.

Within the matrices based on economic distance, the proposal of Molho (1995) is based on the number of employments and the distance between analyzed regions assuming a decrease exponential relation.

In Spain, there are more than 700 employment offices distributed throughout the national territory. In Figure 1 the number of employment offices is represented on the first vertical axis and the number of unemployed by office on the second vertical axis. In the first place we see that the distribution of the employment offices is different in each autonomous region. These differences are related to the size of the provinces and the population density. In second place, in some communities such as Cataluña, Madrid and Valencia, the number of unemployed by office is clearly high.

Figure 1. Number of employment offices and unemployment by EEOO



Source: INEM-SPEE and Spanish Labour Force Survey (EPA).

With this information, we introduce a modification of the spatial weight matrix proposed by Molho (1995) using the number of employment offices in each province as a key aspect. These data introduce the importance of the PES in each province.

In this way, the elements of the proposed spatial matrix are obtained by means of this expression:

$$w_{ij} = \frac{O_j \exp(-D_{ij})}{\sum_{k \neq i} O_k (D_{ik})} \quad (\forall_i \neq j) \tag{0.3}$$

$$w_{ii} = 0$$

O being the number of public employment offices in province j and D the distance between i and j.

In this paper, two different types of spatial weight matrix are considered in order to analyze the sensitivity of the results: a binary matrix based on contiguity criteria ($W^{BINARY-CONTIGUITY}$) and the modification on Molho's matrix ($W^{OFFICES}$).

The next step consists in the detection of the existence of global and local spatial autocorrelation. The most usual tests are Moran[3] (1948) and the Geary c (1954) which are obtained by means of these expressions:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} z_i^2}; \; i \neq j \tag{0.4}$$

$$\text{y } z_i = x_i - \bar{x}, \; S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}.$$

$$c = \frac{(n-1) \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \left(x_i - x_j\right)}{4A \sum_{i=1}^{n} z_i^2} \tag{0.5}$$

4. Empirical results

a. How are filled vacancies distributed in Spain?

The presence of spatial dependence in the data can be easily spotted by mapping the variables of interest: placement by PES and placement not by PES. In the first case, Figure 2 and 4, show the placement levels by PES of the 47 Spanish provinces in 2007 and 2008, respectively.

The map suggests that the provinces with a high participation by the PES are located in the southwest of Spain as well as Madrid and Valencia. In contrast, the presence in absolute terms of the PES is lower in Castilla and León and in the Cantabrian regions, with the exception of Asturias.

In the second case, the distribution of the placements not made by PES is collected for 2007 and 2008 in Figures 3 and 5, respectively. Again, for the provinces of Castilla and León and Castilla-La Mancha the placements are low. On the contrary, the highest values are found in Madrid and Barcelona.

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[3] Both I and c present the classic form of autocorrelation coefficients, i.e. the expression of the covariance between the values analysed in the numerator and its variance in the numerator.

Figure 2. Placement by PES levels in Spain (NUTS3). 2007

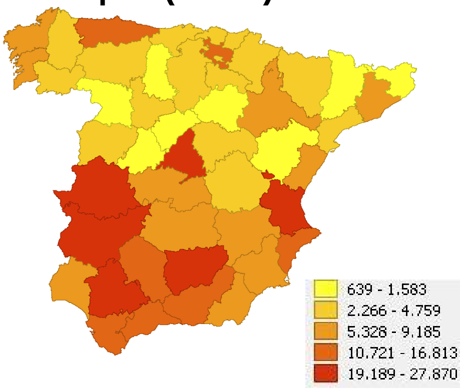


Figure 3. Placement not by PES levels in Spain (NUTS3). 2007

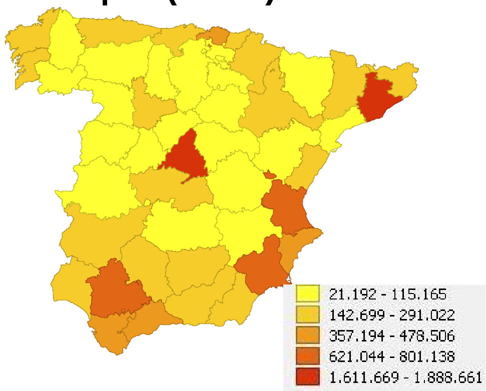


Figure 4. Placement by PES levels in Spain (NUTS 3). 2008

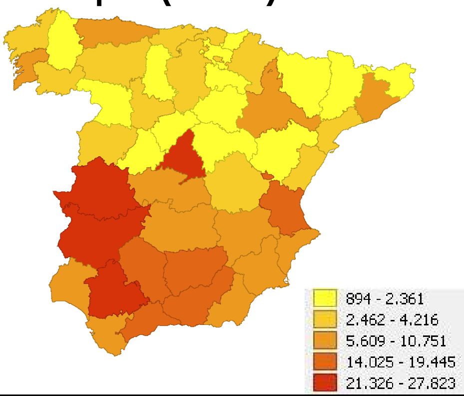
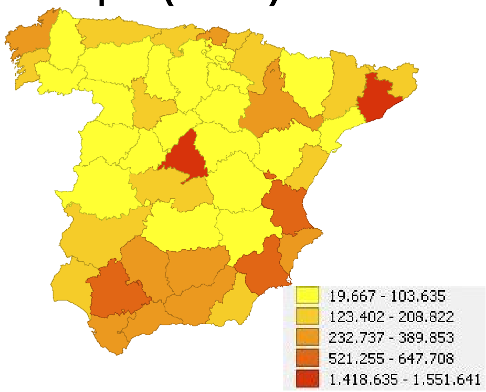


Figure 5. Placement not by PES levels in Spain (NUTS 3). 2008



Before we focus on the analysis of spatial autocorrelation it is important to analyze the following figures. This type of map allows us to classify the provinces in function of the quartile in which they are found given the level of placements. Figures 6 and 8 show the distribution by quartiles of the placements in which the PES intervenes and the distribution of the market placements is in Figures 7 and 9.

The maps show that in the distribution of the placements through the PES, low outliers are not found either in 2007 or in 2008 and 2 provinces stand out as top outliers (Badajoz and Madrid) in 2007 and 5 provinces as top outliers (Cáceres, Badajoz, Sevilla, Córdoba and Madrid) in 2008. Most of the provinces are found at intermediate values, although two geographically different zones can be observed, the northern part and the southern zone, this latter with a higher presence of SPE.

In Figures 7 and 9 (placement not by PES), there are 5 upper outliers (Barcelona, Madrid, Murcia, Sevilla and Valencia) in 2007 and 4 upper outliers (Barcelona, Madrid, Sevilla and Valencia) in 2008.

Figure 6. Box-map of placement by PES 2007

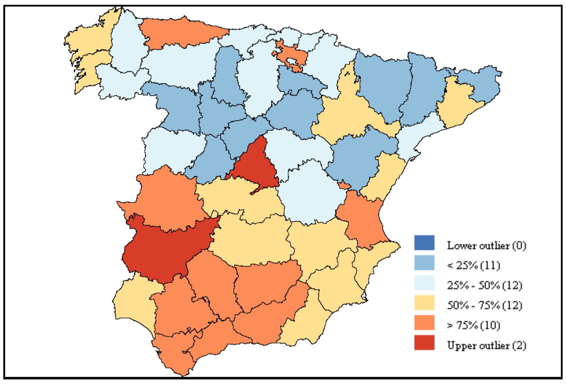


Figure 7. Box-map of placement not by PES 2007

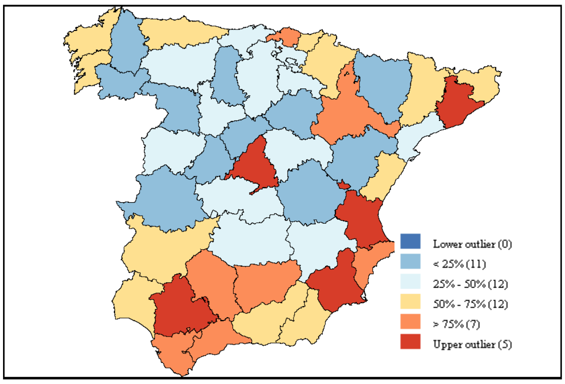


Figure 8. Box-map of placement by PES 2008

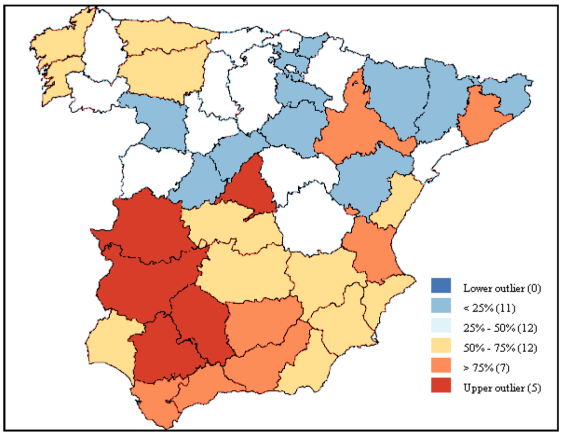
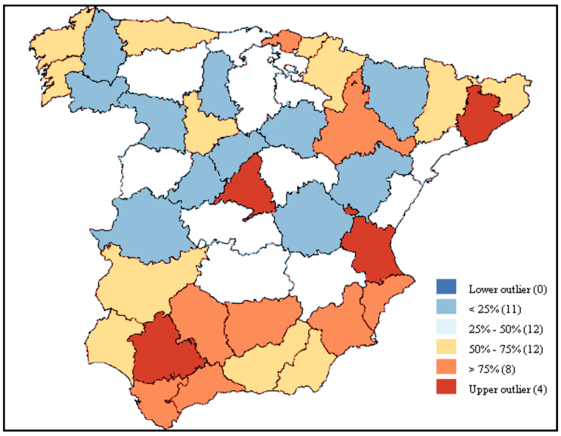


Figure 9. Box-map of placement not by PES 2008



All in all, with the deterioration of the economic cycle the number of provinces constituting the upper outliers has increased and the opposite has happened in the case of placement not by PES. This perhaps suggests the high importance of the placement role of PES in times of crisis.

b. Results of spatial dependence

Measures of global spatial autocorrelation

In this work the question is whether a spatial pattern exists in relation to the two categories of placement and, if it does, whether it is stable in time.

López-Bazo et al. (1999) compare the distribution of the GDP per capita at two moments of time to analyze the existence and later the persistence of spatial inequality, as well as the configuration of the clusters detected. We have opted also for comparing the level of spatial autocorrelation in the years 2007 and 2008.

In this section we have calculated the measures of global spatial autocorrelation most used, such as Moran's I and Geary's for the two categories of **r** placements and also by gender. The fact that women are becoming the main users of PES should be kept in mind at the moment of valuing if their activity is really meaningful.

Moran's I range between -1 and 1 due to the use of the standardized spatial weight matrix. A positive value of Moran's I indicate positive correlation, suggesting the presence of clusters of high or low values of **x**: areas with values of **x** higher than the average tend to be surrounded by areas with values of **x** higher than the average and vice versa. A negative value indicates negative correlation, suggesting that areas with values of **x** higher than the average are generally surrounded by areas with values of **x** lower than the average and vice versa. A value of 0 indicates the absence of spatial autocorrelation (Longhi et al. 2007).

According to the test of Moran and Geary (Tables 2 and 3) in the case of placements by PES, there is evidence to reject the null hypothesis of non spatial autocorrelation while in placements not by PES we cannot reject this hypothesis. This implies that the placements in which PES intervene present a spatial autocorrelation (mainly positive) while in the case of the distribution of the market placements we cannot confirm the spatial autocorrelation.

This result confirms our hypothesis of integration of the placement role of the PES. All in all, two distribution patterns are identified; the differences should be kept in mind at the moment of planning public policies.

Table 2. Measures of global spatial autocorrelation $W^{BINARY-CONTIGUITY}$ (Moran's I)

Variables	2007			2008		
	Moran's I	z-value	Prob.	Moran's I	z-value	Prob.
Placement by PES	0.246	3.019	**0.001*****	0.360	4.351	**0.000*****
Placement not by PES	-0.046	-0.309	0.379	-0.049	-0.348	0.364
Male placement by PES	0.058	0.914	0.180	0.220	2.812	**0.002*****
Male placement not by PES	-0.025	-0.044	0.482	-0.0032	-0.131	0.448
Female placement by PES	0.388	4.607	**0.000*****	0.434	5.171	**0.000*****
Female placement not by PES	-0.058	-0.484	0.314	-0.060	-0.498	0.309

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 3. Measures of global spatial autocorrelation $W^{BINARY-CONTIGUITY}$ (Geary's c)

Variables	2007			2008		
	Geary's c	z-value	Prob.	Geary's c	z-value	Prob.
Placement by PES	0.791	-1.775	**0.038****	0.698	-2.409	**0.008*****
Placement not by PES	0.958	-0.213	0.416	0.949	-0.264	0.396
Male placement by PES	0.995	-0.035	0.486	0.856	-1.030	0.151
Male placement not by PES	0.944	-0.302	0.381	0.942	-0.317	0.376
Female placement by PES	0.639	-3.124	**0.001*****	0.613	-3.182	**0.001*****
Female placement not by PES	0.958	-0.205	0.419	0.949	-0.251	0.401

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

In the case of the placements by PES, Moran's I has increased from 0.25 in 2007 to 0.36 in 2008. If we keep the gender factor in mind, it is relevant that the increase in the number of women placed by PES rises the level of spatial autocorrelation to the value of 0.43 in 2008. Nevertheless, the fact is that the number of jobs filled by men in 2007 is not significant but shows a distribution pattern more similar to the distribution of market placement, whereas in 2008 Moran's I is significant and reaches a value of 0.22. In this year, the economic situation was worse and men go more to the PES.

In Table 4 we show the results of Moran's I but we use the matrix based on Molho (1995). The conclusions are exactly the same, though it is noticeable that the statistical values are higher, especially for the gender factor, in the case of women there is an increase from 0.38 to 0.60 in 2008.

Table 4. Measures of global spatial autocorrelation $W^{OFFICES}$ (Moran's I)

Variables	Moran's I	z-value	2007 Prob.	Moran's I	z-value	2008 Prob.
Placement by PES	0.376	2.210	**0.014****	0.596	3.470	**0.000*****
Placement not by PES	-0.067	-0.287	0.387	-0.083	-0.390	0.348
Male placement by PES	0.187	1.183	0.118	0.457	2.742	**0.003*****
Male placement not by PES	-0.033	-0.069	0.472	-0.0058	-0.226	0.411
Female placement by PES	0.518	2.993	**0.001*****	0.665	3.837	**0.000*****
Female placement not by PES	-0.090	-0.445	0.328	-0.101	-0.516	0.303

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

We obtain similar results (Table 5) [4], when Moran's I is computed on the growth of placement by PES or on placement by PES change.

Table 5. Measures of global spatial autocorrelation $W^{BINARY-CONTIGUITY}$ (Placement by PES)

	Change			Growth		
	Moran's I	**z-value**	**Prob.**	**Moran's I**	**z-value**	**Prob.**
1Q2007	-	-	-	-	-	-
2Q2007	0.270	3.412	**0.000*****	0.290	3.379	**0.000*****
3Q2007	0.097	1.530	**0.063***	-0.048	-0.681	0.248
4Q2007	0.109	1.870	**0.031****	0.276	3.572	**0.000*****
1Q2008	0.016	0.433	0.333	0.135	1.726	**0.042****
2Q2008	0.198	2.546	**0.005*****	0.263	3.141	**0.001*****
3Q2008	0.333	3.944	**0.000*****	0.265	3.567	**0.000*****
4Q2008	0.365	4.364	**0.000*****	0.418	4.928	**0.000*****

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Moran's I placement by PES is positive, that is, it confirms the existence of a spatial pattern and a higher level of integration than in the case of non PES placement.

Measures of local spatial autocorrelation

In this section we identify possible spatial clusters, especially in the case of PES placement so we have calculated the local Moran's I[5].

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[4] See Longhi y Nijkamp (2007).

[5] Anselin (1995) proposes the next expression $I_i = z_i \sum_{j=1}^{J_i} w_{ij} z_j$

The results obtained by local statistician of Getis and Ord (1992) coincide with local Moran's I.

A positive sign signifies the existence of positive spatial autocorrelation, *spatial clustering of high value* or *spatial clustering of low value*. The spatial clusters high-high and low-low capture positive spatial autocorrelation while the spatial outliers high-low and low-high capture the existence of negative spatial autocorrelation. The local Moran's I adopts negative values (juxtaposition of negative and positive values), for example, in Madrid, while it indicates positive spatial autocorrelation in provinces such as Badajoz, Córdoba, Málaga, Sevilla, León or Valladolid.

Again, we use two spatial weight matrixes: $W^{BINARY-CONTIGUITY}$ and $W^{OFFICES}$ in order to verify the results. In the measure in which $W^{OFFICES}$ incorporates the number of employment offices it is logical to think that the results obtained confirm the existence of positive clusters of the type high-high, especially.

Figures 10 and 11 reveal two types of clusters in 2007 and 2008. A cluster of positive values exists (high-high) for the PES in Extremadura and Andalucía, that is consolidated in 2008 with the deterioration of the economic cycle. On the other hand, the cluster of lower values (low-low) diminishes in 2008.

The figure suggests that high- placement by PES regions tends to be located close to other PES high- placement regions, while PES low- placement regions tend to be located close to other PES low- placement ones. These clusters of high and low placement by PES regions might indicate the existence of positive spatial autocorrelation across the PES placements.

Figure 10. Clusters 2007 $W^{BINARY-CONTIGUITY}$ (Placement by PES)

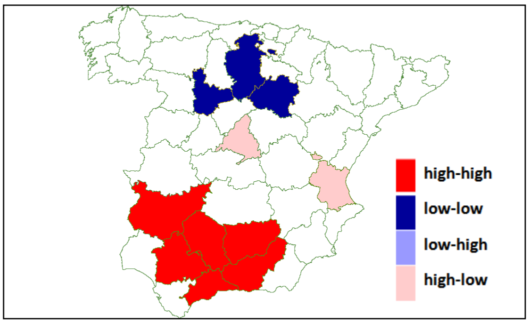


Figure 11. Clusters 2008 $W^{BINARY-CONTIGUITY}$ (Placement by PES)

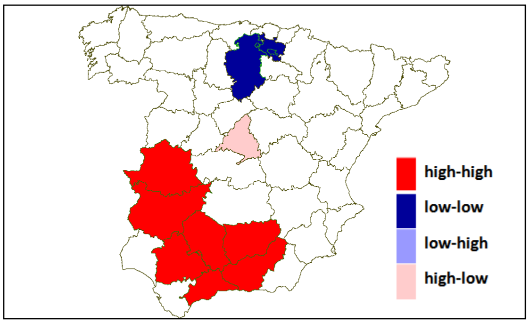


Figure 12. Clusters 2007 $W^{OFFICES}$ (Placement by PES)

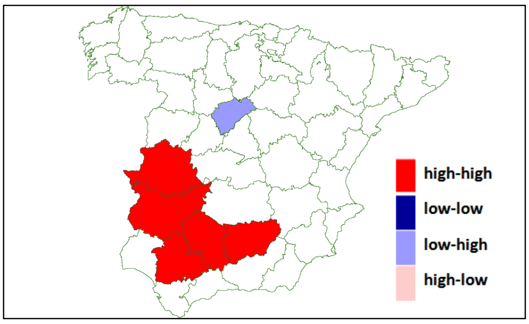
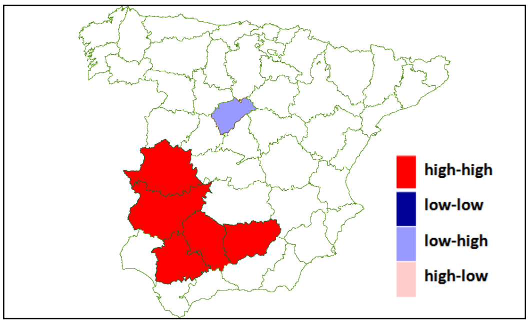


Figure 13. Clusters 2008 $W^{OFFICES}$ (Placement by PES)



When we use the $W^{OFFICES}$ the results support the previous analysis (Figures 12 and 13). The cluster low-low disappears in the provinces of Castilla and León because in these provinces the number of employment offices is above the national average. On the other hand, the cluster high-high is maintained.

Finally, Table 6 collects the values of the local Moran's I in 2007 and 2008 for the placements not by PES. It is observed that spatial independence is only rejected in the case of Madrid and Barcelona. Moran's I indicates the existence of negative spatial autocorrelation. Many Spanish provinces lose population each year and Madrid and Barcelona act as a clear focus of attraction; this is the reason why there are provinces such as high-low spatial outliers.

Table 6. Measures of local spatial autocorrelation $W^{BINARY-CONTIGUITY}$ (Placement not by PES)

	2007			2008		
	Moran's I	z-value	Prob.	Moran's I	z-value	Prob.
Barcelona	-0.895	-1.801	**0.036****	-1.064	-2.143	**0.016****
Madrid	-2.419	-6.476	**0.000*****	-2.431	-6.491	**0.000*****

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Specification of the model: spatial-error model and spatial lag model

In the linear regression model, the existence of spatial dependence can be included in two basic ways. In the first option, the dependent variable is related to the spatial lag variable Wy and this model is known as *spatial lag model*. The specification of the spatial lag model is:

$$y=\rho Wy+X\beta+\varepsilon \tag{0.6}$$

ρ being the spatial autoregressive parameter and $\varepsilon \sim N(0,\sigma^2 I)$. The inclusion of the spatial lag variable Wy on the right hand side of the model causes the inconsistency of the ordinary least squares estimators due to the endogeneity of the model. In this case, it is necessary to apply other estimation methods such as maximum likelihood (ML) or instrumental variables (VI) (Anselin, 1988).

This model is more appropriate when the aim is the assessment of the existence and strength of spatial interaction. Each value of spatially lagged variable is not only correlated with the error term associated with this location, but with all of them.

The second option consists of the specification of a spatial process in the perturbation term; the error term is related to its spatial lag error $W\varepsilon$. The immediate consequence of this is the existence of a non-spherical error covariance matrix and the least squares estimators are unbiased but inefficient. The most common approach is the inclusion of a spatial autoregressive process:

$$\begin{aligned} y&=X\beta+\varepsilon \\ \varepsilon&=\lambda W\varepsilon+\zeta \end{aligned} \tag{0.7}$$

where λ is the spatial autoregressive coefficient for the error lag $W\varepsilon$ and $\xi \sim N(0, \sigma^2 I)$. This type of model is adequate to include the spatial autocorrelation due to measurement errors or to variables that are not crucial in the model (nuisance dependence)[6].

In first place, we tried to obtain an empirical model in order to explain the behaviour of the placements by PES in the Spanish provinces. Our data source is the Spanish National Statistic Institute (INE). We propose two alternatives for the explanatory variables. On the one hand, the independent variables are the Gross Domestic Product per capita at market prices (thousands of €) of the previous year and the level of unemployment (Model A). On the other hand, the GDPpc and the population density are proposed as explanatory variables (Model B). Economic theory and practice suggest that the activity of PES is higher when the economic situation is worse. We expect an anti-cyclic behaviour and GDPpc is included to check this hypothesis. The population density is included to test the role or the effect of urban agglomeration on the PES behaviour.

Model A	$y = \beta_0 + \beta_1 GDPpc(-1) + \beta_2 UNEM + \epsilon$ (0.8)
Model B	$y = \beta_0 + \beta_1 GDPpc(-1) + \beta_2 DEN + \epsilon$ (0.9)

Secondly, these models are estimated by means of OLS and the existence of spatial autocorrelation on the residuals is tested by the usual tests: the Moran test and the tests based on the Lagrange Multiplier (LM). One of the key aspects in spatial econometrics is the possible different behaviours of the specification tests. In order to analyze the sensitivity of the results of the specifications test with different spatial weight matrix, two specifications of the spatial weight matrix are considered: the binary matrix based on geographic contiguity and the $W^{OFFICES}$.

As observed in Table 7, the results of the Moran test are significant and reject the hypothesis of non spatial autocorrelation in both years and using the two alternatives for the spatial weight matrix previously defined. In spatial econometric literature there is a wide discussion about different strategies to select models: particular to general or vice versa. In this paper, we applied the particular to general strategy which is reviewed by Florax et al. (2003) based on LM LAG and ERROR statistics and the robust option proposed by Anselin et al. (1996).

Firstly, the LM test is applied in order to detect the existence of spatial dependence due to an omitted spatial lag or due to a spatial autoregressive error process. If both tests are significant, the model is selected based on the results of the robust LM test.

The results of LM test show the spatial lag model as the best specification when the spatial weight matrix based on geographic contiguity is considered but the spatial error model is the best model if the $W^{OFFICES}$ are applied to summarize the spatial dependence. But the values of the LM LAG and ERROR statistics are quite similar and as a consequence we decided to estimate both specifications.

[6] There are other specifications for the spatial error process; see Cliff and Ord (1981) and Kelejian and Robinson (1993).

Table 7. Results of the specification tests in 2007 and 2008

	Model A 2007		Model B 2007	
	CONTIGUITY	OFFICES	CONTIGUTITY	OFFICES
Moran errors	1.960 (**0.049**)**	2.793 (**0.005**)***	1.796 (**0.072**)*	2.692 (**0.007**)***
Lm-lag	3.642 (**0.056**)*	3.763 (**0.052***)	4.340 (**0.037**)**	5.185 (**0.022**)**
Lm-error	1.575 (0.209)	6.216 (**0.012**)**	1.443 (0.229)	5.844 (**0.015**)**
R LM LAG	2.094 (0.147)	0.012 (0.909)	3.226 (**0.072**)*	0.267 (0.605)
R LM ERROR	0.026 (0.869)	2.465 (0.116)	0.330 (0.565)	0.926 (0.335)

	Model A 2008		Model B 2008	
	CONTIGUITY	OFFICES	CONTIGUITY	OFFICES
Moran errors	2.983 (**0.002**)***	4.543 (**0.000**)***	2.219 (**0.026**)**	3.149 (**0.001**)***
Lm-lag	5.748 **(0.016)****	9.053 (**0.002**)***	5.932 (**0.014**)**	8.690 (**0.003**)***
Lm-error	5.634 (**0.017**)**	17.499 (**0.000**)***	2.696 (**0.100**)*	8.178 (**0.004**)***
R LM LAG	1.020 (0.312)	0.097 (0.754)	3.412 (**0.064**)*	0.863 (0.352)
R LM ERROR	0.906 (0.341)	8.543 (**0.003**)***	0.176 (0.674)	0.351 (0.553)

P-value are in parenthesis

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

The estimated models for the PES placement in 2007 and 2008 are summarized in Table 8 and Table 9 respectively.

With 2007 data, all the explanatory variables are statistically significant and the sign of the estimated coefficient matches with its expected value. Then PES activity is going to be reduced if the economic activity is quite high or the level of unemployment is decreasing whereas the PES placements increase with population density. The positive sign of the estimated coefficient for the population density variable shows the relevancy of the PES placement role in urban areas.

As the results of the specification tests had indicated, there are very slight differences between the models when they are estimated even though it is possible to assert some differences between the spatial lag and spatial error models. Then, if the contiguity matrix is considered, the spatial autoregressive parameter in the spatial error model is more significant than the spatial autoregressive parameter in the spatial lag model.

From an economic perspective, the most interesting results are the estimations of the spatial parameter, since these values summarize the role of spatial dependence through the spatial lag variable and spatial lag error, respectively. As is shown in Table 9 and Table 10, these coefficients are positive and significant but the intensity of spatial dependence is not very high. The positive value for the spatial autoregressive coefficient is consistent with the exploratory data analysis realized over the PES placement where a positive spatial autocorrelation was detected.

Then, the estimated values for ρ range between 0.173 y 0.063 if the contiguity matrix is applied whereas these values range between 0.168 and 0.270 with $W^{OFFICES}$. For the spatial error specification, the spatial autoregressive coefficient varies between 0.068 and

0.065 with contiguity matrix whereas these values increase when the $W^{OFFICES}$ are considered (0.262 and 0.212).

When the same models are estimated with 2008 data the coefficients are similar to the 2007 models (Table 9). In this year, we find different behaviour between both spatial specifications. When the *UNEM* variable is included as regressor the asymptotic t statistic for the spatial autoregressive coefficient is higher whereas in the spatial lag model the asymptotic t statistic is higher when the *DEN* variable is considered as regressor. In general, a slight increase of the spatial coefficient and signification level is detected.

Table 8. Results of the OLS estimation, spatial lag and spatial error with SPE 2007 data

		CONTIGÜITY		OFFICES			CONTIGÜITY		OFFICES	
	OLS	**Spatial lag**	**Spatial error**	**Spatial lag**	**Spatial error**	**OLS**	**Spatial lag**	**Spatial error**	**Spatial lag**	**Spatial error**
Constant	15325.998***	11663.142***	12809.387***	11748.115***	13044.221***	25074.692***	18107.215***	21502.555***	20599.194***	20778.660***
	(4.138)	(3.147)	(2.915)	(3.166)	(3.334)	(5.826)	(3.689)	(4.071)	(5.000)	(4.404)
GDP pc(-1)	-627.601***	-509.624***	-512.574**	-512.361***	-507.921**	-1136.374***	-886.890***	-969.872***	-988.264***	-902.275***
	(-3.164)	(-2.714)	(-2.151)	(-2.726)	(-2.364)	(-4.616)	(-3.586)	(-3.244)	(-4.456)	(-3.376)
Unemployed	0.117***	0.114***	0.118***	0.114***	0.177***					
	(6.419)	(6.770)	(6.617)	(6.770)	(7.240)					
Density						30.620***	30.74***	30.796***	30.722***	30.110***
						(5.333)	(5.820)	(5.766)	(5.958)	(6.350)
R2	0.517	0.497	0.525	0.498	0.582	0.433	0.469	0.466	0.417	0.529
Spatial ρ		0.173**		0.168**			0.063**		0.210**	
		(2.129)		(2.076)			(2.084)		(2.437)	
Spatial λ			0.065*		0.212**			0.068*		0.262***
			(1.683)		(2.176)			(1.783)		(2.783)
Log likelihood		-448.341	-449.438	-448.337	-447.992		-452.263	-453.327	-451.547	-451.401

Notes: number of observations: 47.
t Statistics are in parenthesis (absolute values)
* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 9. Results of the OLS estimation, spatial lag and spatial error with SPE 2008 data

		CONTIGÜITY		OFFICES			CONTIGÜITY		OFFICES	
	OLS	Spatial lag	Spatial error	Spatial lag	Spatial error	OLS	Spatial lag	Spatial error	Spatial lag	Spatial error
Constant	17871.663***	9641.156**	13833.955***	11381.710***	12125.74***	26301.395***	17684.062***	21017.802***	19320.742***	20385.286***
	(5.023)	(2.220)	(2.905)	(3.364)	(3.458)	(5.980)	(3.523)	(3.684)	(4.720)	(4.198)
GDPpc (-1)	-729.128***	-430.355**	-581.461**	-499.308***	-442.965**	-1114.674***	-804.689***	-883.468***	-866.699***	-811.819***
	(-4.167)	(-2.256)	(-2.440)	(-3.260)	(-2.424)	(-4.819)	(-3.433)	(-2.981)	(-4.259)	(-3.209)
Unemployed	0.080***	0.077***	0.084***	0.075***	0.083***					
	(6.329)	(6.601)	(7.092)	(6.746)	(9.967)					
Density						24.926***	24.581***	25.09***	23.85***	23.69***
						(4.305)	(4.701)	(4.561)	(4.817)	(5.266)
R2	0.547	0.555	0.630	0.482	0.787	0.391	0.431	0.453	0.382	0.539
Spatial ρ		0.071***		0.270***			0.073**		0.274***	
		(2.644)		(3.568)			(2.440)		(3.112)	
Spatial λ			0.108***		0.508***			0.085**		0.316***
			(3.628)		(7.276)			(2.432)		(3.514)
Log likelihood		-445.377	-444.759	-442.846	-436.643		-452.152	-453.268	-450.399	-450.624

Notes: number of observations: 47.

t Statistics are in parenthesis (absolute values)

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

The existence of spatial clusters corroborated in the results presented above show the presence of spatial heterogeneity in PES placement. From an econometric point of view spatial heterogeneity causes instability of the parameters and/or heterocedasticity. One of options to control this problem consists of the specification of a variable parameter model but, in this case, the sample size is too low and we decided to introduce dummy variables associated with each CCAA with the aim of capturing site-specific characteristics (Brunsdon et al., 1998). Then, for example, a variable *Andalucía* is generated with a value 1 if the province is below this CCAA or if not, a value 0.

This method allows including spatial heterogeneity in the form of differentiated cluster patterns across space. In this case, two clusters have been previously identified (Figure 10 and 11) which correspond with two different zones in terms of PES behaviour.

At first, we estimated these models by means of OLS including as explanatory variables the dummy variables previously defined together with the two sets of quantitative variables considered in this paper. There are only five CCAA with statistically significant effect: Castilla y León, Castilla-La Mancha, Extremadura, Galicia and Madrid. The hypothesis of spatial and non spatial autocorrelation is tested on the residuals of these models by means of the habitual specification test whose results are summarized below.

Table 10. Results of the specification tests with dummy variables in 2007 and 2008

	Model A 2007		Model B 2007	
	CONTIGUITY	OFFICES	CONTIGUITY	OFFICES
Moran errors	2.424 (**0.015**)**	1.577 (0.115)	1.075 (0.282)	1.218 (0.223)
Lm-lag	2.639 (**0.100**)*	1.391 (0.238)	3.108 (**0.078**)*	1.926 (0.165)
Lm-error	0.733 (0.392)	0.801 (0.371)	0.002 (0.964)	0.017 (0.894)
R LM LAG	1.972 (0.160)	0.625 (0.429)	5.388 (**0.020**)**	1.772 (0.183)
R LM ERROR	0.066 (0.798)	0.035 (0.851)	2.282 (0.131)	0.323 (0.569)

	Model A 2008		Model B 2008	
	CONTIGUITY	OFFICES	CONTIGUITY	OFFICES
Moran errors	3.327 (**0.000**)***	3.066 (**0.002**)***	1.467 (0.142)	1.697 (**0.089**)*
Lm-lag	6.989 **(0.008**)***	4.804 (**0.028**)**	6.527 (**0.010**)**	4.326 (**0.037**)**
Lm-error	3.039 (**0.081**)*	5.371 (**0.020**)**	0.141 (0.707)	1.056 (0.304)
R LM LAG	4.003 (**0.045**)**	1.021 (0.312)	8.471 (**0.004**)***	3.389 (**0.065**)*
R LM ERROR	0.526 (0.818)	1.587 (0.207)	2.084 (0.148)	0.118 (0.731)

In 2007, it is possible to assert that there is no evidence of spatial autocorrelation when the dummy variables are introduced in the specification with the spatial weight matrix $W^{OFFICES}$. The results of the specification tests vary slightly depending on the criteria chosen to define the spatial weights. Then, the hypothesis of no spatial autocorrelation is rejected if the contiguity matrix is included for the computation but the level of significance is not very high.

In the 2008 sample, the results of the specification test reject the hypothesis of no spatial autocorrelation with spatial weight matrix and the spatial lag specification is indicated as more appropriate.

The estimated models by means of ML method for the PES placement in 2007 and 2008 are summarized in Table 11 and Table 12, respectively.

The estimated coefficients have the expected sign as in the first proposed models. An anti cyclic behaviour of the role of the PES is tested since the marginal effects of GDP pc and unemployment on PES placement are negative and positive, respectively. In Table 12 the results of the estimates relating to the 2008 data are shown. In this case, the spatial error model behaves betters if the variable unemployment is included as regressor whereas the spatial lag model is the best alternative when the density variable is considered. In general terms, a small increase on the spatial externalities is detected. Then, the spatial autoregressive coefficient in the spatial lag model ranges between 0.071 and 0.274 whereas the range of variation is greater in the spatial error specification (0.108 and 0.508).

With these results, we can conclude that the placement role of the PES presents both spatial autocorrelation and spatial heterogeneity. Then, it is necessary to include the effect of spatial location in the analysis of the PES.

Table 11. Estimation results by means of ordinary least squares, spatial and spatial error with 2007 PES data including regional dummies

		CONTIGUITY		OFFICES			CONTIGUITY		OFFICES	
	OLS	**Spatial lag**	**Spatial error**	**Spatial lag**	**Spatial error**	**OLS**	**Spatial lag**	**Spatial error**	**Spatial lag**	**Spatial error**
Constant	22512.406***	16631.519***	19323.237***	20096.672***	21866.983***	30662.231***	24578.288***	30706.995***	28080.240***	30415.142***
	(5.551)	(3.661)	(4.454)	(5.015)	(5.722)	(8.527)	(5.742)	(9.462)	(7.749)	(8.927)
GDP pc (-1)	-864.407***	-657.705***	-749.248***	-785.847***	-841.164***	-1280.316***	-1070.624***	-1281.866***	-1200.868***	-1271.417***
	(-4.601)	(-3.412)	(-3.548)	(-4.417)	(-4.672)	(-6.659)	(-5.449))	(-7.387)	(-6.680)	(-7.008)
Unemployment	0.072***	0.073***	0.083***	0.073***	0.076***					
	(3.428)	(3.936)	(4.414)	(3.864)	(4.031)					
Density						19.646***	20.165***	19.623***	20.158***	19.940***
						(3.643)	(4.286)	(3.994)	(4.209)	(4.134)
C. Mancha	-4747.413**	-5928.537***	-4778.604**	-4414.669**	-4380.414**	-5963.439	-7211.638***	-5965.818***	-5584.421***	-5766.392***
	(-2.065)	(-2.781)	(-2.092)	(-2.149)	(-2.042)	(-2.759)	(-3.626)	(-3.045)	(-2.911)	(-2.862)
C. León	-5080.798***	-4347.989***	-4616.684**	-4779.126***	-4985.459***	-5477.429***	-4680.119***	-5485.383***	-5113.503***	-5415.823***
	(-2.829)	(-2.689)	(-2.446)	(-2.944)	(-3.001)	(-3.199)	(-3.027)	(-3.543)	(-3.323)	(-3.414)
Extremadura	6536.963**	6622.352***	7467.163***	6253.488***	6469.580***	6177.158**	6284.062***	6158.094***	5878.642*	6131.292**
	(2.465)	(2.833)	(3.108)	(2.619)	(2.594)	(2.389)	(2.783)	(2.617)	(2.542)	(2.537)
Galicia	-6009.539**	-4251.549*	-4920.099*	-5352.065**	-5849.155**	-7978.093***	-6145.725***	-8000.094***	-7265.139***	-7936.979***
	(-2.514)	(-1.883)	(-1.946)	(-2.452)	(-2.525)	(-3.493)	(-2.848)	(-3.873)	(-3.486)	(-3.637)
Madrid	13003.294**	12586.172**	11180.376**	12616.103**	12115.602**	15321.502***	14790.625***	15312.375***	14780.520***	14944.404***
	(2.284)	(2.518)	(2.156)	(2.481)	(2.365)	(2.984)	(3.293)	(3.275)	(3.241)	(3.212)
R square	0.729	0.7316	0.736	0.725	0.728	0.731	0.755	0.731	0.739	0.733
Spatial ρ		0.051*		0.089			0.054*		0.101	
		(1.797)		(1.249)			(1.940)		(1.408)	
Spatial λ			0.071*		0.074			-0.003		0.051
			(1.853)		(0.713)			(-0.062)		(0.489)
Log likelihood		-435.921	-436.743	-436.611	-437.050		-434.949	-436.647	-435.655	-436.515

Notes: number of observations: 47.
t Statistics are in parenthesis (absolute values)
* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 12. Estimation results by means of ordinary least squares, spatial and spatial error with 2008 PES data including regional dummies

		CONTIGUITY		OFFICES			CONTIGUITY		OFFICES	
	OLS	**Spatial lag**	**Spatial error**	**Spatial lag**	**Spatial error**	**OLS**	**Spatial lag**	**Spatial error**	**Spatial lag**	**Spatial error**
Constant	24253.149***	15765.780***	13296.214***	19895.369***	21388.638***	31624.879***	23180.662***	30921.207***	27339.855***	31149.847***
	(6.832)	(4.062)	(2.893)	(5.832)	(6.243)	(9.834)	(5.979)	(9.636)	(8.199)	(9.784)
GDP pc (-1)	-925.217***	-627.361***	-585.962***	-774.955***	-827.088***	-1236.371***	-941.969***	-1211.515***	-1088.229***	-1218.005***
	(-6.211)	(-4.087)	(-2.754)	(-5.541)	(-5.328)	(-7.803)	(-5.699)	(-7.662)	(-7.159)	(-7.823)
Unemployment	0.048***	0.047***	0.064***	0.048***	0.061***					
	(3.377)	(3.947)	(5.864)	(3.879)	(5.503)					
Density						12.559**	12.694***	12.782***	12.507***	12.705***
						(2.629)	(3.186)	(2.954)	(3.038)	(3.078)
C. Mancha	-4927.687**	-6417.518***	-6731.219***	-4366.656***	-3173.189*	-6503.933***	-7927.193***	-6427.181***	-5954.699***	-6121.356***
	(-2.522)	(-3.732)	(-3.265)	(-2.620)	(-1.714)	(-3.383)	(-4.713)	(-3.509)	(-3.605)	(-3.336)
C. León	-4147.731***	-3331.263***	-4345.219**	-3638.643***	-3504.415***	-5053.248***	-4199.056***	-4960.234***	-4557.233***	-4860.073***
	(-2.728)	(-2.584)	(-2.499)	(-2.791)	(-2.610)	(-3.328)	(-3.221)	(-3.353)	(-3.464)	(-3.411)
Extremadura	8984.094***	8663.291***	8207.592***	8021.219***	7656.902***	8041.363***	7765.824***	7925.728***	7095.495***	7631.606***
	(4.015)	(4.635)	(4.713)	(4.105)	(3.566)	(3.505)	(4.052)	(3.773)	(3.528)	(3.473)
Galicia	-5937.584***	-3560.602**	-3123.225	-4906.718***	-5470.822**	-7994.615***	-5620.635***	-7705.832***	-6981.466***	-8012.301***
	(-2.932)	(-1.951)	(-1.323)	(-2.773)	(-2.397))	(-3.959)	(-3.039)	(-3.911)	(-3.866)	(-3.935)
Madrid	12800.866***	12286.994***	6237.004	12122.167***	9179.626**	18609.874***	17861.507***	18750.805***	17955.589***	18185.257***
	(2.481)	(2.862)	(1.446)	(2.754)	(2.268)	(2.984)	(4.685)	(4.520)	(4.584)	(4.488)
R square	0.799	0.814	0.860	0.798	0.842	0.779	0.814	0.781	0.794	0.787
Spatial ρ		0.072***		0.152**			0.071***		0.149**	
		(2.992)		(2.340)			(2.872)		(2.179)	
Spatial λ			0.161***		0.309***			0.028		0.114
			(12.750)		(3.414)			(0.648)		(1.108)
Log likelihood		-425.143	-425.115	-426.218	-425.446		-427.433	-430.884	-428.722	-451.401

Notes: number of observations: 47.
t Statistics are in parenthesis (absolute values)
* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

5. Conclusions

This analysis has special importance due to the culmination of the transfer process of the active labour market policy to the autonomous regions. We show in this paper that the spatial structure of placement is rather complex. Our analysis provides a first step towards understanding the distribution of the vacancies filled due to the mediation of PES. The result reveals increasing spatial concentration of placement by PES in Spain. The simple values of the Local Moran's I statistic are only meaningful for a few regions but enough to identify two types of clusters.

The hypothesis of this research is that if the PES labour market is integrated, we would expect to see very similar results amongst neighbouring regions. Our results show that we find spatial dependence only when the job offers are registered with the PES and match with a job seeker included in the Data Bank of job seekers.

In the year 2007, we can identify a cluster of provinces with positive values (spatial clustering of high value) formed by Badajoz, Sevilla, Córdoba and Málaga that increases in 2008 and a cluster of provinces with negative values (León, Palencia, Burgos and Valladolid), that in 2008 decreases. This suggests that the behaviour of the PES is counter cyclical. Finally, it is important to consider space explicitly when we analyze the work of the PES. This means that the values with a higher value in terms of PES placements tend to be located together in space and the values with a lower value also.

There is an important market for the PES in the southwest of Spain, perhaps connected with agriculture. However, in Castile and León the importance of the PES is decreasing. In the case of market placements we cannot reject spatial independence. Nevertheless, at local level, Madrid and Barcelona are spatial outliers. It is important to indicate the heterogeneous nature of the Spanish labour market and the differences between provinces.

The results suggest that, in the case of PES placement, high unemployment rates foster spatial clustering of high values.

Notes

The models in this article have been estimated using different software. The non spatial models and spatial models have been estimated using Matlab. The Moran and Geary statistics have been computed with Stata 10. The maps have been executed with GEoDa and Geographic Information System.

References

ALBERT, C., TOHARIA, L. (2007): "Las estadísticas administrativas como fuentes de información para el estudio del mercado de trabajo andaluz", Instituto de Estadística de Andalucía.

ALUJAS RUIZ, J.A. (2007): "El servicio público de empleo y su labour como intermediario en el mercado de trabajo en España", Cuadernos de Ciencias Económicas y Empresariales, 53, 27-51.

ANSELIN, L. (1988): *Spatial econometrics methods and models*. Ed. Kluwer Academic Publishers.

ANSELIN, L. (1995): "Local indicators of spatial association-LISA", Geographical Analysis, 27 (2), 93-115.

BANDE, R., FERNÁNDEZ, M., MONTUENGA, V. (2008): "Regional unemployment in Spain: Disparities, business cycle and wage setting", *Labour Economics*, 15, 885-914.

BRUNSDON, C., FOTHERINGHAM S., CHARLTON, M. (1998): "Geographically weighted regression-modeling spatial non-stationarity", *The Statistician*. 47, 431-43.

BRUTTEL, O. (2005): "Are employment zones Successful? Evidence from the first four years", Local Economy, 20(4), 389-403.

CASE, AC., ROSEN, HS., HINES, JR. (1993): "Budget spillovers and fiscal policy interdependence evidence from the states", *Journal of Public Economics*, 52, 285-307.

CLIFF, A.D., ORD, J.K. (1973): "Spatial autocorrelation", Pion, London.

CLINCH, J.P., O'NEILL, E. (2009): "Applying spatial economics to national spatial planning", *Regional Studies*, 43(2), 157-178.

DE KONING, J., DENYS, J. Y WALWEI, U. (1999): "Deregulation in Placement Services: A Comparative Study for Eight EU Countries", Comisión Europea, D. G. de Empleo.

DECRESSIN, J. Y FATÁS, A. (1995): "Regional labour market dynamics in Europe", *European Economic Review*, 39, 1627-1655.

ELHORST, J.P. (2003): "The mystery or regional unemployment differentials: theoretical and empirical explanations", *Journal of Economic Surveys*, 17(5), 709-748.

ELHORST, J.P. (2008): "A spatiotemporal analysis of aggregate labour force behaviour by sex and age across the European Union", Journal of Geographical System, 10, 167-190.

FAHR, R., SUNDE, U. (2005): "Regional dependencies in job creation: an efficiency analysis for western Germany", IZA DP 1660.

FERRO-LUZZI, G., FLÜCKIGER, Y. (2003): "Performance measurement of efficiency of regional employment offices", National Research Project 45.

GETIS, A.; ORD, J.K. (1992): "The Analysis of Spatial Association by Use of Distance Statistics", *Geographical Analysis* 24, p. 189-206.

GREGG, P. Y WADSWORTH, J. (1996): "How effective are state employment agencies? Jobcentre use and job matching in Britain", *Oxford Bulletin of Economics and Statistics*, 58(3), 443-467.

GRIFFITH, D.A., WONG, D., WHITFIELD, T. (2003): “Exploring relationships between the global and regional measures of spatial autocorrelation”, *Journal of Regional Science*, 43(4), 683-710.

IBOURK, A., MAILLARD, B., PERELMAN, S., SNEESSENS, H.R. (2001): “The matching efficiency of regional labour markets. A stochastic production frontier estimation, France 1990-1995”, IZA DP 339.

JIMENO, J.F., BENTOLILA, S. (1998): “Regional unemployment persistente (Spain, 1976-1994)”, *Labour Economics*, 5, 25-51.

JIMENO, J.F. (1993): “La reforma del Instituto Nacional de Empleo como mecanismo de intermediación en el mercado de trabajo”, *Boletín del Círculo de Empresarios*, 57, 235-252.

JOASSART- MARCELLI, P., GIORDANO, A. (2006): “Does local access to employment services reduce unemployment? A GIS analysis of One-Stop Career Centers”, *Policy Sciences*, 39, 335-359.

KARLSSON, CH., HAYINES, K. (2002): “Regional labour markets in transition”, *Papers in Regional Science*, 81, 301-304.

LÁZARO SÁNCHEZ, J.L. (2003): “El Servicio Andaluz de Empleo”, *Temas laborales: Revista andaluza de trabajo y bienestar social*, 68, 9-26.

LONGHI, S., NIJKAMP, P. (2007): “Forecasting regional labour market developments Ander spatial autocorrelation”, *International Regional Science Review*”, 30, 100-119.

LÓPEZ-BAZO, E., DEL BARRIO, T., ARTIS, M. (2002): “The regional distribution of Spanish unemployment: A spatial analysis”, *Papers in Regional Science,* 81, 365-389.

LÓPEZ-BAZO, E., VAYÁ, E., MORA, A.J., SURINACH, J. (1999): “Regional economic dynamics and convergence in the European Union”, *The Annals of Regional Science*, 33, 343-370.

LUNDIN, M. Y SKEDINGER, P. (2006): “Decentralisation of active labour market policy: The case of Swedish local employment service committees,” *Journal of Public Economics*, 90 (4-5), 775-798.

MAYOR,M.,LÓPEZ, A.J. (2008): “Spatial shift-share analysis versus spatial filtering: an application to Spanish employment data”, Springer, 34 (1), 123-142.

MOLHO, I. (1995): “Spatial autocorrelation in British unemployment”, *Journal of Regional Science*, 35(4), 641-658.

MORAN, P. (1948): The interpretation of statistical maps, *Journal of the Royal Statistical Society B* 10:243-251.

OSBERG, L. (1993): “Fishing in Different Pools: Job-Search Strategies and Job-Finding Success in Canada in the Early 1980s”, Journal of Labour Economics, 11(2), 348-386.

OVERMAN, H.G., PUGA, D. (2002): “Unemployment clusters across Europe’s regions and countries”. *Economic Policy*, 17(34), 115-148.

RUIZ ÁLVAREZ, J.L. (1993), “La Reforma de los Servicios Públicos de Empleo: el caso del INEM”, *Hacienda Pública Española, Cuadernos de Actualidad*, I/1993, 10-14.

SHELDON, G.M. (2003): “The efficiency of public employment services: a nonparametric matching function analysis for Switzerland”, *Journal of Productivity Analysis*, 20, 49-70.

VASSILIEV, A., FERRO LUZZI, G., FLÜCKIGER, Y. Y RAMIREZ, J.V. (2006): “Unemployment and employment offices´ efficiency: what can be done?”, *Socio-Economic Planning Sciences*, 40, 169-186.

WALWEI, U. (1996): “Improving job-matching through placement services”, en Schmid, G., O’Reilly, J. y SCHÖMANN, K. (Eds.) (1996): *International Handbook of Labour Market Policy and Evaluation.* Cheltenham, R.U., Edward Elgar, 402-430.