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The accessibility to Employment Offices in the Spanish labour market

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The accessibility to Employment Offices in the Spanish labor market

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Abstract:

This paper relies upon the theoretical framework of spatial economics to analyze regional unemployment rate disparities in Spain. We use administrative regional aggregate data to explore the distribution of unemployed workers and local unemployment rates in the 8,109 Spanish municipalities in 2009.

Also, we connect this distribution with the location of employment offices in Spain. Hence, the main purpose of our paper is to evaluate the role of the Public Employment Service (PES) in local labor markets by considering the physical distance to employment offices and the spatial structure of their catchment areas. Firstly, we propose a new accessibility measure and, secondly, we estimate a spatial model so as to explain the aforementioned disparities and test whether higher accessibility to employment offices could contribute to reduce local unemployment rates. We also analyze different levels of accessibility to employment offices across the national territory and propose improvements in the PES performance.

Keywords: Employment Offices, unemployed, accessibility.

JEL: J68, J60, C21, R12.

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1. Introduction

After a fifteen-year period of sustained reduction in the Spanish unemployment rates and convergence with most EU countries, the economic downturn has sent Spain back to the top of countries with higher unemployment rates. There is a public outcry for a labor reform which may address the core problems in our labor market and modify issues such as the current active labor market policies (ALMPs). These policies, which also cover the PES, have been hardly evaluated, so there is little information available about their effectiveness.

Whenever figures of registered vacancies are considered, the Spanish PES efficiency is regarded as low. This poor performance may be partly explained by the small number of job counselors. In 2006, there were 1,837 mil. unemployed and just 7,996 employees at PES offices (CES, 2009) in Spain. Consequently, each counselor saw about 230 unemployed—one of the highest records in the EU— and the unemployed were likely to compete for time with their counselor.

In 1998, the Spanish government started to decentralize the PES to the autonomous communities, which were granted complete authority on ALMPs¹. However, to ensure standards of service provision regardless of place of residence, PESs in the autonomous communities have remained integrated in the National Employment System. The decentralization of ALMPs was undertaken so that each region adopted a needs-based approach which could bring in better management of the available resources, and adapted employment and training programmes to the features of its labor market and unemployed profile.

With respect to the PES, in theory it provides unemployed easy access to employers and labor markets at local, regional, national and European level. According to the European Commission, the main task of any PES is to ensure that no job-seeker is marginalized by a lack of adequate assistance to find suitable employment.

Placement services are located in space, hence analyses of the accessibility to employment offices require spatially explicit tools. Also, any improvements in accessibility would translate into better PES performance, so we need to discuss whether the accessibility to employment offices is really equitable regardless of place of residence. Also, recent planning, evaluation and policy analyses have devoted more attention to accessibility measures.

This paper focuses on the spatial distributions of unemployed and public employment offices in Spain, and the degree of correspondence between them. Clearly, the distribution of public employment offices in the territory may lead to differences in accessibility for the unemployed and, in turn, have effect on the PES performance.

Studies on the efficiency of PES offices at local level have been done in Germany (Hagen, 2003), Switzerland (Sheldon, 2003) and Sweden (Althin and Behrenz, 2004). However, these studies have not analyzed whether the spatial distribution of employment offices ensures equal access to such offices. In Spain there are no studies of employment offices at local level and, as in other countries (Fertig et al., 2006), we do not know how public funding is distributed among the offices.

¹ The devolution of this power to the Basque regional government will put an end to this decentralization process.

This paper attempts to bridge this gap by combining the methodology of spatial economics with new accessibility measures that take into account the size of a employment office catchment area, so that any difference in access may be adequately tackled. The choice of an accessibility measure is, therefore, crucial for this type of analysis (see Talen and Anselin, 1998).

The outline of the paper is as follows: Section II describes the data used in the paper and examines basic features of the unemployed and employment offices in Spain. It also introduces the accessibility measures proposed. Section III presents comparative evidence of the spatial distributions of unemployed and employment offices across the Spanish municipalities. In Section IV we estimate an unemployment rate equation which includes the accessibility to employment offices as explanatory variable. Section V concludes with some policy recommendations.

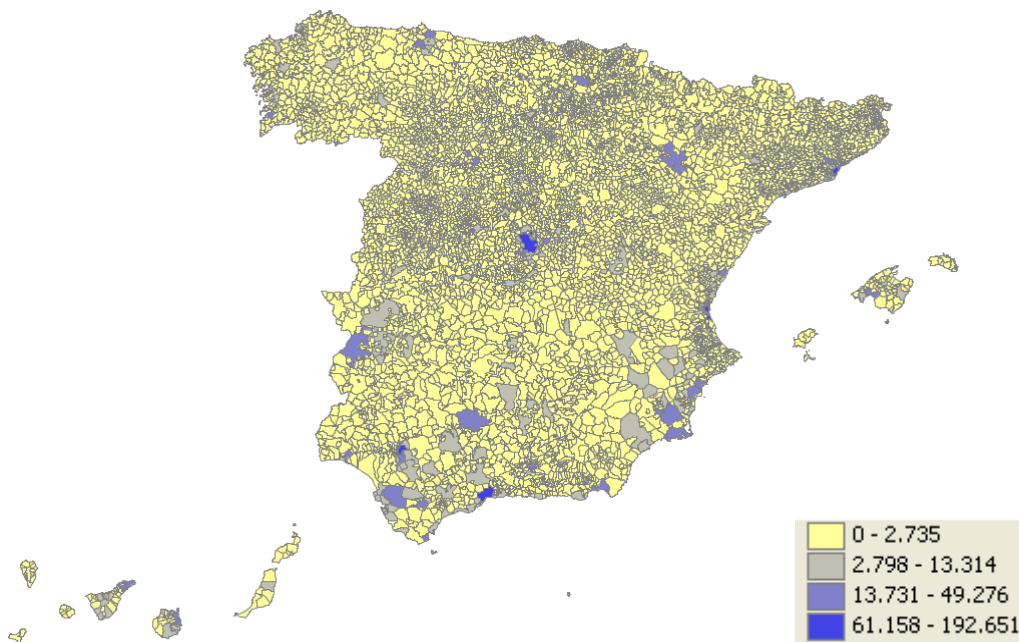
2. Data and methodology

2.1. Data

Unemployment data in the following pages have been taken from the Official Unemployment Statistics, which are published monthly by the INEM-SPEE. Data referring to the local employment offices and their catchment areas have been taken from the regional employment authorities websites and the INEM-SPEE website.

High regional unemployment rates have been endemic in Spain (for a more detailed discussion, see e.g. Jimeno and Bentolila 1998, Bande et al. 2008, Garcia-del-Barrio and Gil-Alana, 2009). Figure 1 displays the map of the 2009 average local unemployment rates in Spain. Over 25% of the unemployed reside in less than 20 municipalities, especially Madrid, Barcelona, Seville, Malaga and Valencia.

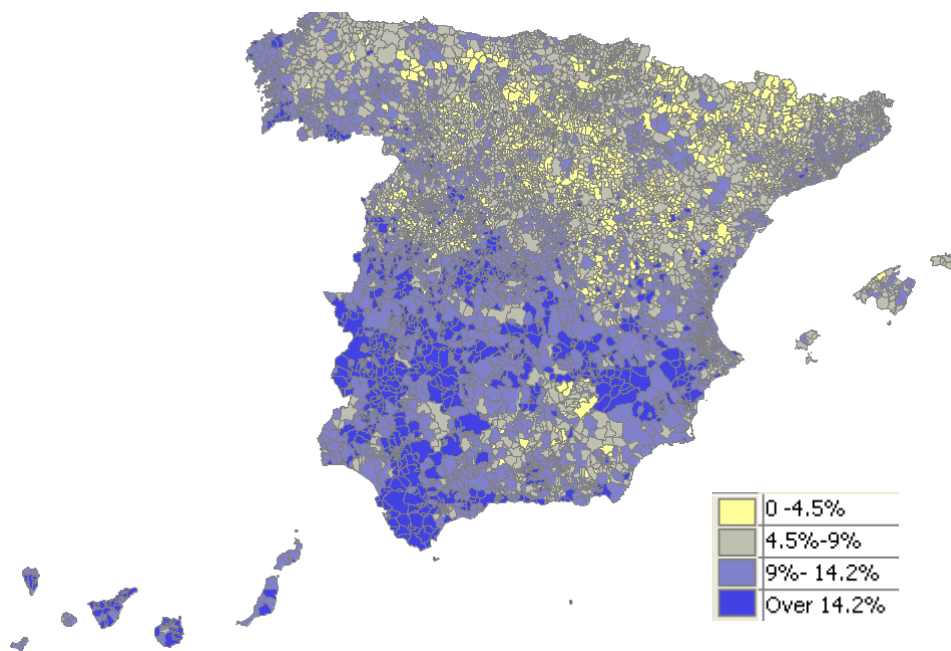
Figure 1. Unemployed population by municipalities (2009 average)



Naturally the evolution of the workforce is of paramount importance when the spatial distribution of the unemployed is considered. No data are available on local unemployment rates because the Labor Force Survey (INE) is sample-based and hence data are not gathered in every Spanish municipality. Nevertheless, even if local unemployment rates could be calculated by approximation, the absolute number of unemployed workers would still be extremely important, since the number of unemployed constitutes a natural limit to the performance of employment offices².

Figure 2 displays the 2009 average of absolute local unemployment rates (unemployed population/ total population of working age). In relative terms, we may clearly see that high unemployment rates are markedly concentrated in the southern regions and along the Mediterranean coast of Spain.

Figure 2. Absolute unemployment rate by municipalities (2009 average)

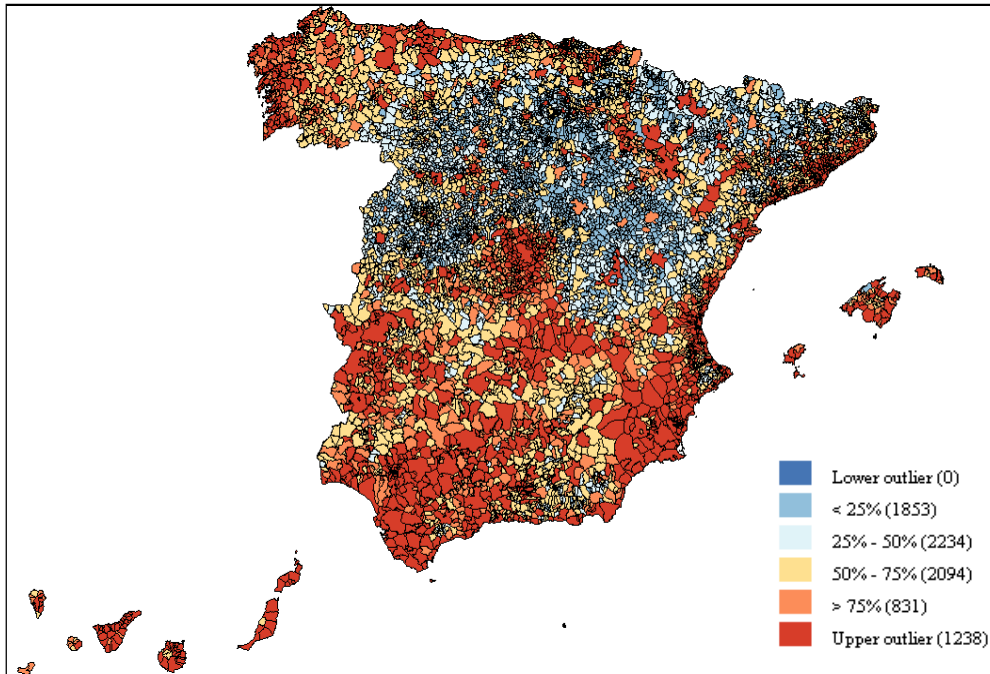


Job counselors at employment offices may only see a limited number of beneficiaries. The Special Plan for Job Counseling, Professional Training and Work Placement estimates that 1,500 new job counselors —approx. two counselors per office— would render a coefficient of 3.5 beneficiaries per counselor and day. Even though the hiring of 1,500 job counselors has led to a significant increase in staff since 2008, current staff numbers are far from meeting the counseling and mediation needs of the unemployed, especially at employment offices that have to attend to a high number of jobless. It is essential to establish clusters of unemployed people at local level, since active job-seeking policies and the modernization of PESs should be more intense in such municipalities.

² Sheldon (2003) assesses the efficiency of placement services in Switzerland using the absolute number of jobless assigned to each of the 126 placement offices.

The box map³ below (Figure 3) shows a concentration of high local unemployment rates, and especially upper outliers (1,238), in the south, Galicia, Asturias and along the Mediterranean coast. Broadly speaking, the map also shows a concentration of low local unemployment rates in Castile and Leon, as well as Aragon (except Zaragoza), Cuenca and Guadalajara.

Figure 3. Box map of local unemployment rates (2009 average)



In any case, the current location pattern of public employment offices in Spain stems from political decisions over the last thirty years. More precisely, employment offices are administrative units established long before the autonomous communities took over ALMPs. The question is whether this location pattern is the most adequate and, if not, how it could be possibly improved. In 2008, the government of the Autonomous Community of Navarre opened a new employment office in Tudela as part of their Plan for the Modernization of the Employment Service of Navarre. Since then the office has provided service to 21 municipalities, as well as the municipality of Tudela itself. Besides alleviating the workload of the employment offices which had to attend to these jobless up to 2008, the office represents a step forward in the autonomy the autonomous communities have been conferred to modernize the PES and improve job counseling and work placement services.

Figure 4 shows the spatial distribution of employment offices in Spain. Clearly, its most striking feature is the large number of municipalities lacking employment offices —7,524 out of 8,109 (see Table 1).

³ See Anselin (1994, 1997), and Talen and Anselin (1998). A box map is a choropleth quartile map augmented with the identification of outliers (those observations in the lowest and highest quartile that fall outside the fences, that is, 1.5 times IQR higher than the third quartile or lower than the first quartile).

Figure 4. Employment office location



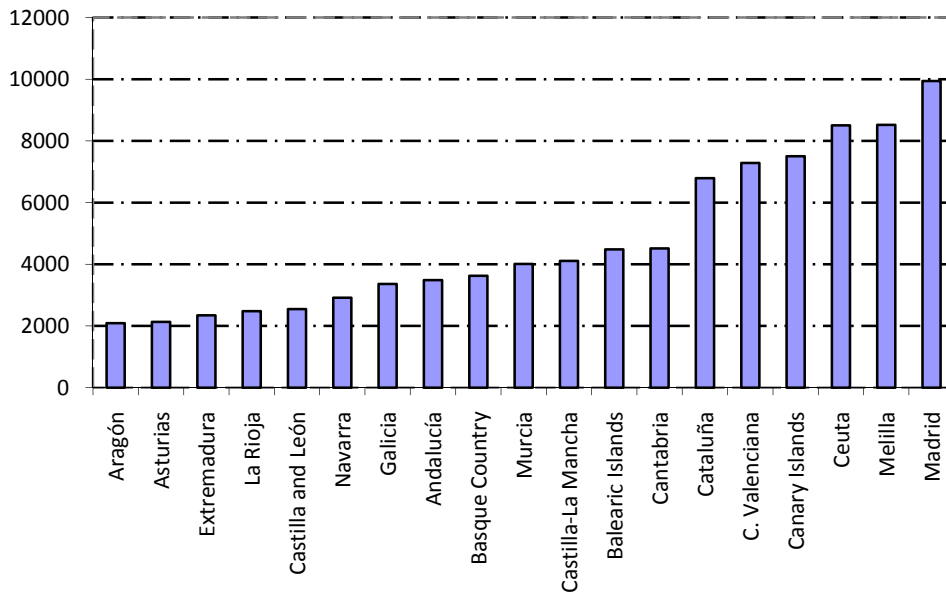
The many municipalities with zero employment offices are predominantly concentrated in Castile and Leon, whereas the nonzero ones are in the south and the south-east, Madrid and Barcelona. Notwithstanding that, a slight dehomogenization of these data shows employment offices in every municipality with over 4,000 jobless, except Paterna and Milasta (Valencia metropolitan area), San Vicent del Raspeig (Alicante metropolitan area), Mijas (Malaga) y Los Realejos (Tenerife).

Table 1. Distribution of the 718 employment offices

Number of municipalities with...	Employment offices
7524	0
526	1
35	2
10	3
6	4
2	5
2	6
2	8
1	11
1	19
Total: 8109	Total: 718

Graphic 1 permits the assertion that there are huge differences between CCAA in terms of unemployed per employment offices. Spain is composed in 17 autonomous communities, each of which has different cultural traditions, political government and different PES, and 2 autonomous cities (Ceuta and Melilla). The number of employment offices appears to be too small with respect to the unemployed they manage, especially in Community of Madrid, Canary Islands, Community of Valencia and Catalonia so that we can expect differences in terms of accessibility.

Graphic 1. Average unemployed per placement office. NUTS-1 (2009)



2.2. Measuring accessibility

One of the aims of this paper is to assess whether the accessibility to employment offices is equitable in Spain. The core issue we have to address is the measure of accessibility itself. Several authors from different perspectives have analyzed the concept of accessibility within the framework of urban and regional economies. For instance, Krugman (1991) and Fujita et al. (1999) study the importance of accessibility in economic development from a regional perspective. Most existing studies on accessibility belong to the field of transportation economy. Gutierrez (2001) and Holl (2007) analyze accessibility improvements in Spain. From a theoretical perspective, Geurs and Van Wee (2004) review is remarkable for its analysis of the usefulness of accessibility measures in the evaluation of changes in transportation infrastructures and its use by researchers and policy makers alike. With respect to labor markets, accessibility measures are given consideration in few works. For instance, Van Wee et al. (2001) develop a concept of accessibility to analyze whether jobs are accessible for employees. Détang-Dessendre and Gagné (2009) study the impact of the place of residence on unemployment duration. They rely on an accessibility measure to convey workers' competition for jobs and subsequently tackle labor market tightness. Joassart-Marcelli and Giordano (2006) use a geographic information system to look into the location of One-Stop Centers in Southern California and their level of accessibility. Consequently, their research is closely related to ours. As far as we know, in Spain there is no research on the spatial distribution of employment offices and their levels of accessibility.

It is currently intended that active employment policies become an asset in the fight against unemployment, so that assurance of equal access to employment offices is essential. We may begin by stating that, even though employment offices are administrative units that were created long ago, their spatial distribution is by no means random. However, regardless of the fact that it does follow a pattern, such distribution may cause either equity or inequity of

access to the offices. By equity we mean that the level of accessibility to employment offices is not to be lower in those municipalities with bad labor market conditions (i.e. high unemployment rates) and, within such municipalities, accessibility conditions should be the same regardless of the autonomous community of residence —whose government, in turn, is responsible for the administration of the employment offices. All the unemployed should be equally treated, wherever they live. In our case, spatial equity is just equal access to employment offices.

That leads us not only to calculate the accessibility to employment offices but also to analyze their spatial distribution. Similarly, Talen and Anselin (1998)⁴ analyze the accessibility measures from a methodological point of view and take into account the spatial dimensions of equity. Their main conclusion is that accessibility measures must be chosen with care when the spatial distribution of a given service is analyzed.

The simplest measure to analyze unemployed accessibility to employment offices consists in counting the existing employment offices within a given area. As we explained above, Figure 4 shows the distribution of employment offices in Spain. It is remarkable that the number of employment offices is higher in the south and the south-east.

However, these measures, based on the count of employment offices per municipality, do not take into account other spatial interactions such as the inverse relation existing between the size of an employment office catchment area and its level of accessibility. Catchment areas are set by counting the number of unemployed assigned to an employment office —i.e. by adding up the number of jobless in the municipalities serviced by a given employment office⁵. In the case of Spain, every unemployed is assigned an employment office depending on their place of residence by the National Employment Authority. Gravity potential, average travel cost and minimum distance also take into account the relation between origin and destination.

Consequently, we need further accessibility measures, similar to those that transcend the mere count of employment offices. Geurs and Van Wee (2004) classifies these as location-based accessibility measures.

Next, we will consider two more types of accessibility measures (also called gravity-based measures). The first type of measure only takes into account the number of employment offices for each regional labor office and the distance to the municipality in which the corresponding employment office is located. The limited scope of this measure leads us to propose a new accessibility measure which also takes into account the number of unemployed within each employment office catchment area. We would like to have had access to the number of job counselors and/or counseling sessions per number of unemployed, but access to this information is not provided at local level.

The first type of measure (denoted by the superscript 'l') is based on the number of employment offices in the same regional labor office, adjusted for the distance between a municipality i and its corresponding employment office.

$$A_i^{la} = EO_j \left(e^{-\lambda d_{ij}} \right) \quad (1)$$

⁴ Talen and Anselin (1998) utilize a case-study on the location of playgrounds in order to analyze the spatial equity in Tulsa, OK.

⁵ In municipalities where job-seekers can choose between two employment offices, they have been assigned the closest one.

Where A_i is a measure of the accessibility to the employment offices in the municipality i in the regional labor office j , EO_j is the number of employment offices in the regional labor office j , d_{ij} is the distance between the municipality i and that in which is located the employment office the unemployed living in i have to go to, measured as the Euclidian distance between the municipalities' centroids. Finally, λ is a parameter of the distance-decay function.

This parameter determines the degree of interaction between the place of residence of the jobless and the employment office they have to go to, the accessibility quality decreasing as distance to the office increases. We have no data on trips to the employment offices, so we have been unable to set the parameters of the distance-decay function. Even though several values were used for this parameter whilst doing this paper, the performance of a sensitivity analysis led us to the results presented here, which were eventually obtained using the following values: $\lambda = -0.10$ and $\lambda = -0.25$ ⁶. Nevertheless, it should also be noted that results do not vary significantly when we use either parameter, especially when we analyze the spatial distribution of accessibility, as it will be shown later.

The study of the internal accessibility or 'self-potential' of employment offices presents further problems, since there are no data on the exact distance λ to the office when unemployed are assigned an office within their municipality of residence. This issue has been studied by some authors (Bröcker, 1989; Frost and Spence, 1995). Furthermore, Zwakhals et al. (1998) proposes a measure of this distance based on the surface of the areas considered. In our study, this variation rendered the results unreliable, so we imputed a value of 1 for these municipalities (7.2% out of total), once the distribution of d_{ij} had been considered.

Accessibility levels have also been calculated using the gravity potential measure, so that we could use other well-known expressions.

$$A_i^{lb} = \frac{EO_j}{d_{ij}^\alpha} \quad (2)$$

In this case, α is a parameter of the distance-decay function. The higher the value of the parameter, the greater will be the resulting differential between nearby and distant municipalities. This value crucially depends on the type of activity involved (Holl, 2007). Higher values are usually assigned to accessibility measures of public services. In this study, the parameter has been set to a value of 2 and 1.5⁷.

We have refined these measures by including the number of employment offices together with the distance and size of their catchment areas. Consequently, the proposed accessibility measure is more empirically adequate, since some employment offices attend to approx. 20,000 jobless —e.g. Fuenlabrada (Madrid)—, whilst others attend to just 1,000 jobless —e.g. Caudete (Albacete)—. The accessibility to employment services is determined by this fact and that cannot be overlooked.

⁶ Joassart-Marcelli and Giordano (2006) establishes $\lambda = -0.25$.

⁷ Bruinsma and Rietveld (1993), Gutierrez (2001) and Holl (2007) assume $\alpha = 1$ in their respective analyses of the accessibility to economic activity.

The second type of measure (denoted by the superscript 'II') is based on the weights of the number of employment offices per unemployed within a catchment area, adjusted for the distance between the municipality i and its corresponding employment office.

$$A_i^{IIa} = \left[\frac{EO_j}{\sum_{i \in j} u_i} (e^{-\lambda d_{ij}}) \right] \rightarrow A_i^{IIa} = [w_j (e^{-\lambda d_{ij}})] \quad (3)$$

Where A_i is the municipality accessibility, w_j is the number of employment offices (EO_j) per employment office catchment area ($\sum_{i \in j} u_i$), measured as the number of unemployed in the

municipalities i within a single catchment area. Finally, d_{ij} is the distance between a municipality i and its corresponding employment office, and λ is a parameter of the distance-decay function. The possible range of values to which that parameter may be set were established above.

Similarly, the index A_i^{Ib} has been modified so that we may know which municipalities implement active labor market policies more extensively. The higher the value of w_j , the greater is the potential of the employment office for providing better service.

$$A_i^{Ib} = \left[\frac{EO_j}{\sum_{i \in j} u_i} / d_{ij}^\alpha \right] \rightarrow A_i^{Ib} = [w_j / d_{ij}^\alpha] \quad (4)$$

Again, α is a parameter of the distance-decay function and adopts the values set before.

Once the accessibility measures have been defined, the following step consists of analyzing their spatial distribution.

3. Accessibility measure clustering

The methodology used in this paper to analyze the geographical differences in access to employment services relies upon the exploratory spatial data analysis (ESDA). This type of analysis allows us to identify the main clusters of municipalities with higher numbers of unemployed and test whether the level of accessibility to employment offices is also higher in them. Talen and Anselin (1998) point out the advantages of using a LISA indicator and focus on the fact that this facilitates the detection of relevant patterns of local spatial association. Knox (1989) defines a spatial cluster as «*a geographically bounded group of occurrences of sufficient size and concentration to be unlikely to have occurred by chance*». Tsou et al. (2005) also recommends a spatial analytical perspective to evaluate suitability of urban public facilities in assessing whether or not, or to what degree, the distribution of urban public facilities is equitable.

Within the field of labor market studies, several contributions have taken into account the spatial dimension of regional labor markets and pointed out the high degree of interdependence of local labor markets (e.g. Molho, 1995). Patacchini and Zenou (2007)

analyze the reasons for the spatial dependence in local unemployment rates. This spatial autocorrelation is mainly due to the fact that the unemployed may seek and find work in different areas, so spatial interactions result from the mobility of the unemployed. This paper adds consideration of spatial dependences in local unemployment rates to the diverse influences exerted by public employment services across different levels of accessibility.

Using the information available, we intend to compare the spatial distribution of the unemployed and the existing clusters of unemployed with the distribution of offices, so that we may establish the degree of matching between the two distributions. Notwithstanding that, not only is the spatial pattern of the offices relevant, but more complex aspects must also be taken into account, such as those relating to the accessibility indices calculated. Ideally, accessibility to employment offices should be kept at an adequate level even in high unemployment rate contexts —in other words, there should be no clusters of municipalities with low accessibility levels.

This section examines global and local spatial autocorrelations in local unemployment rates, employment offices and accessibility measures. Our main purpose is to identify the specific patterns that may arise from these autocorrelations —spatial clusters, outlier regions— and analyze the overlapping patterns of the variables considered.

Firstly, we analyze the existence of spatial autocorrelations using Moran’s I and the randomization approximation (Cliff and Ord, 1981). Table 2 displays Moran’s I for municipality unemployment rates and the accessibility measures defined previously.

Since the statistics are significant, all the variables show positive spatial autocorrelation, which suggests the existence of spillovers across municipalities, that is, the spatial structure of these variables is clear, each of them is not scattered randomly and independently in space.

Table 2. Measure of global spatial autocorrelation (Moran’s I)

Variables		I	Z
Unemployed people		0.147	24.334
Absolute local unemployment rate		0.574	85.300
Employment offices*		0.119	18.214
A_i^{Ia}	$(\lambda = 0.1)$	0.618	91.427
	$(\lambda = 0.25)$	0.505	75.891
A_i^{IIa}	$(\lambda = 0.1)$	0.625	92.272
	$(\lambda = 0.25)$	0.624	91.711
A_i^{Ib}	$(\alpha = 2)$	0.142	21.562
	$(\alpha = 1.5)$	0.165	25.126
A_i^{IIb}	$(\alpha = 2)$	0.057	8.891
	$(\alpha = 1.5)$	0.076	11.738

Notes : All statistics are significant at the 1% level. The expected value for Moran’s I is $-1.234e-04$.

*We also applied Moran’s I to the square root transformed employment offices variable due to the large number of municipalities without employment offices ($I=0.137$; $Z=20.230^{***}$). The conclusion is the same when BB joint-count statistics and Empirical Bayes test are computed (EB, Assunção y Reis,1999): the p-value is 0.001 and 0.016 respectively.

3.1. The spatial distribution of the unemployed

Once the null hypothesis of spatial randomness has been rejected, two additional questions are raised: where are the clusters and what is their spatial extent (Fisher and Getis 2010). Both questions are answered with the help of exploratory spatial data analysis (ESDA), namely the local version of Moran's I, LISA (Anselin, 1995). This measure of spatial autocorrelation describes the degree of similarity or dissimilarity between values in spatially close areas.

The local version of Moran's I for each municipality is computed as follows:

$$I_i = \frac{z_i}{\sum_i z_i^2 / n} \sum_j w_{ij} z_j; \quad z_i = x_i - \bar{x}$$

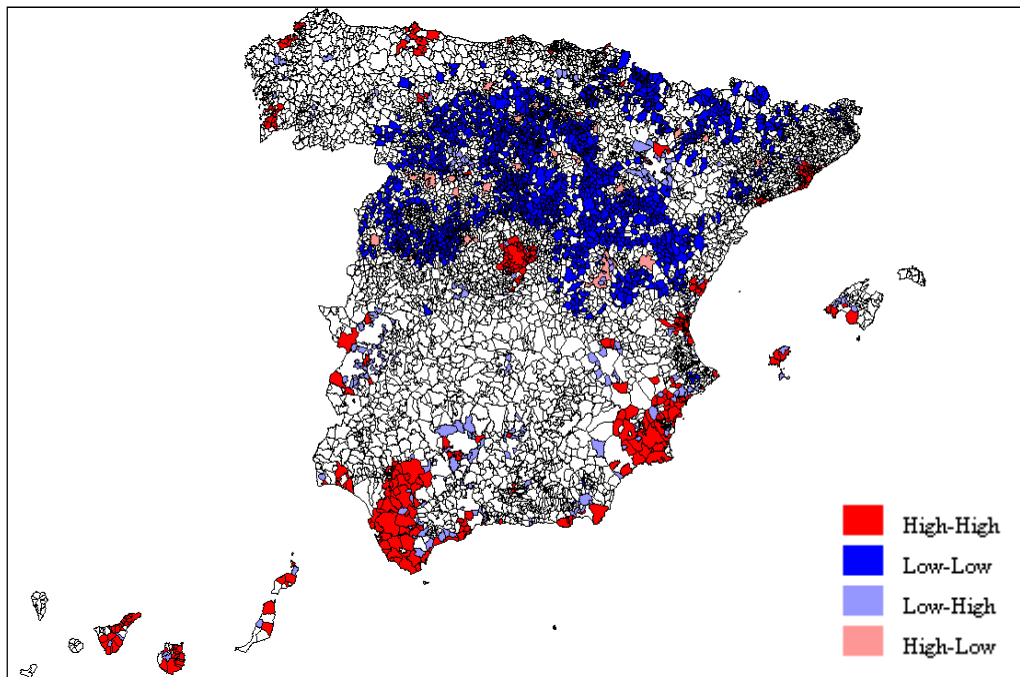
Where the observations z_i and z_j are in deviations from the mean and the summation over j is such that only neighboring values of i are included.

A positive value for I_i indicates spatial clustering of similar values (high or low), whereas a negative value indicates spatial clustering of dissimilar values between a region and its neighbors. In this case, inference is based on the conditional permutation approach as consequence of the existence of global spatial autocorrelation (Anselin, 1995).

Figure 5 shows the LISA map for unemployed in Spain for 2009. The figure suggests that high unemployment regions tend to be close to other high unemployment regions. Most significant high-high (HH) municipalities are located in southern Andalusia (Cadiz and some other municipalities), Murcia, central Asturias, Madrid, Barcelona, Tenerife and Las Palmas de Gran Canaria, among others.

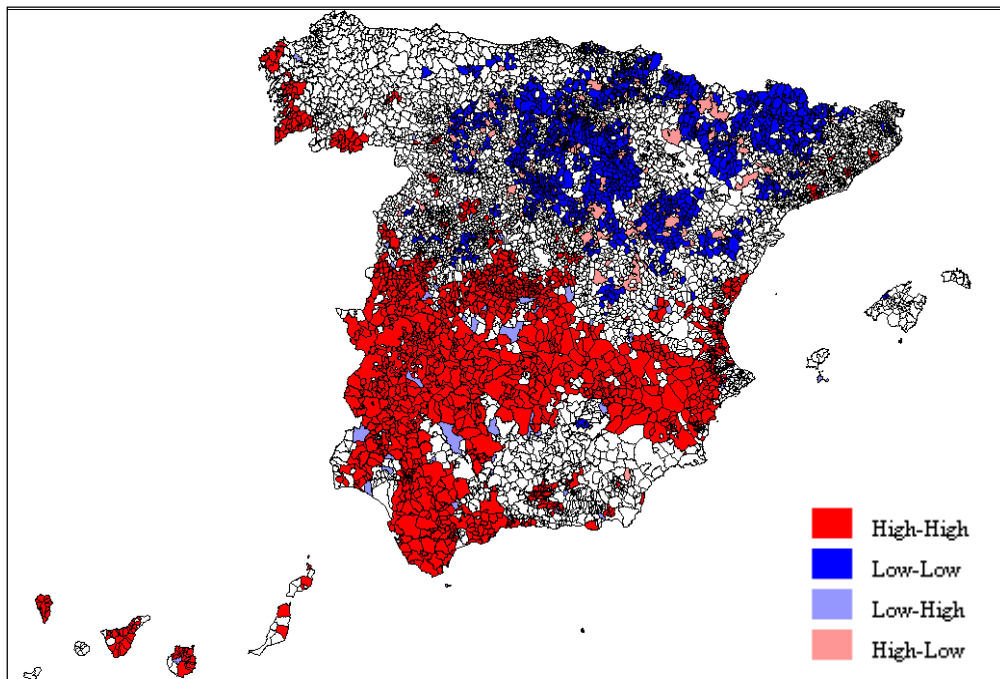
The map also points to the existence of clusters of low-low (LL) municipalities. Most significant LL municipalities are located in Castile and Leon, Guadalajara and Aragon (especially in Teruel). These are municipalities of the LL type of spatial regime —i.e. municipalities where unemployment rates are significantly below average— which, in turn, are surrounded by municipalities with similar rates. These clusters of HH and LL regions indicate the existence of positive spatial autocorrelations across the observations of our data set.

Figure 5. LISA map for unemployed people (2009)



As regards the LISA map for absolute local unemployment rates (Figure 6), it seems that Spanish municipalities are characterized by positive spatial autocorrelation, same as in the case of the levelled variable. In this case, the clusters (HH and LL) are made up of a greater number of municipalities, and two areas stand out very clearly: HH in the south and LL in the north-east. The map also reveals the existence of some atypical municipalities, characterized by negative spatial autocorrelation (juxtaposition of negative and positive values). For example, some municipalities in Castile and Leon and Aragon perform much worse than their neighbors, since they are significantly HL.

Figure 6. LISA map for absolute local unemployment rates (2009)



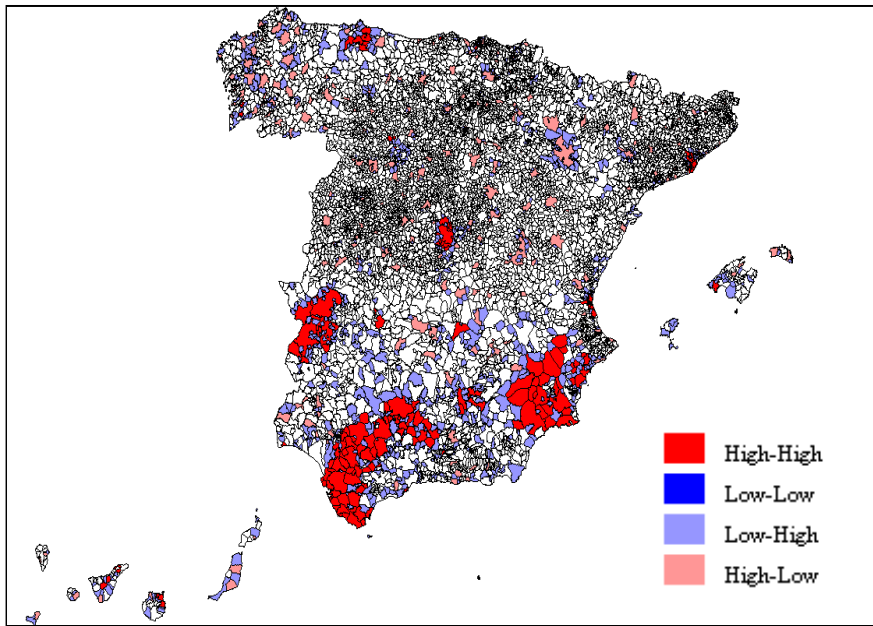
3.2. Spatial distribution of the employment offices

Below we analyze the clusters of municipalities according to the number of employment offices within their territory. Our purpose is to establish a relation between these clusters and those of unemployed, and test whether the employment offices are located in municipalities where there are positive spatial autocorrelation, namely HH clusters. Since this variable does not conform to a normal distribution (7,254 out of 8,109 municipalities have no employment offices), we have transformed it by calculating its square root (Talen and Anselin, 1998).

There is a clear pattern of HH spatial clustering in the south (Seville, Cordoba and Cadiz), Valencia, Alicante, Murcia, Barcelona, Madrid, central Asturias and Extremadura. The existence of HL municipalities and the non-existence of LL clusters is good in terms of equity, for it ensures the existence of an employment office nearby any municipality. In other words, there are no big clusters of municipalities lacking employment offices. Figures 5, 6 and 7 confirm the overlapping between HH spatial clusters of unemployed and employment offices. Employment offices are located around the municipalities with high unemployed, this distribution may be called efficiency but it is not equitable.

Nevertheless, limiting the measure to the number of employment offices is far too simple, since we need to consider some other issues which also have an effect on employment offices accessibility.

Figure 7. LISA map for employment offices



3.3. Results based on the comparison of accessibility indices

Finally, this section compares the accessibility measures proposed by resorting again to Moran's local indicators (LISA). Generally speaking, decreases in accessibility should be expected as we proceed further away from major towns.

Figure 8 shows the LISA maps for the accessibility indices A_i^{Ia} (upper half of the page) and A_i^{IIa} (lower half of the page). In both cases, the parameter values have been set to $\lambda = -0.10$ and $\lambda = -0.25$. When we examine the LISA for the A_i^{Ia} index, in which only the number of employment offices and the distance have been considered, we notice the presence of HH clusters that are coincidental with those in Figures 5 and 7.

However, when the number of employment offices per catchment area w_j is taken into account, the A_i^{IIa} index shows a different spatial distribution. In this case, the HH and LL clusters are not coincidental with those detected using the A_i^{Ia} index, but they include municipalities not necessarily linked to major cities. Therefore, when we take into account the number of unemployed people, previously detected HH accessibility clusters disappear in Madrid, Barcelona and their metropolitan areas, as well as Extremadura, Cadiz, the Balearic Islands and the Canary Islands. For example, there is an HH cluster in western Asturias, since the municipalities in this area present a good w_j indicator and reasonable distance rates.

The most interesting results are obtained when we analyze the LL clusters detected especially in the Autonomous Community of Madrid, along the Mediterranean coast, as well as Toledo, Zaragoza, the Balearic Islands and the Canary Islands. This is due to the fact that, even though most employment offices are concentrated in urban areas, as is the case in Barcelona and its metropolitan area, these offices are not sufficient to attend to the high number of

unemployed from the city itself and the surrounding municipalities, who also have to travel to the offices. Therefore, the relation w_j is very low in these municipalities.

Figure 9 shows the LISA maps for the accessibility indices A_i^{Ib} (upper half of the page) and A_i^{IIb} (lower half of the page). In both cases, the parameter values have been set to $\alpha = 2$ and $\alpha = 1.5$. When we examine the LISA for the A_i^{Ib} index, in which only the number of employment offices and the distance have been taken into account, we may notice that, in general, some HH clusters are coincidental with the HH clusters detected using the accessibility index A_i^{Ia} and, therefore, with those in Figures 5 and 7.

In the case of the accessibility index A_i^{IIb} , its spatial pattern does not differ greatly from that of the index A_i^{Ib} . It should be noted that clusters in Madrid, Barcelona, Valencia, Extremadura and central Asturias cease to be HH, but not those in Andalusia. There is no relevant difference with respect to LL clusters.

Even though it is true that some HH clusters in the two above charts disappear when we take into account the number of unemployed people, the HH cluster in Cadiz remains and western Asturias becomes an area with high levels of accessibility to employment offices. As regards the LL clusters, there is no relevant difference between the A_i^{IIb} and the A_i^{Ib} indices. The results show the influence of the proposed functional form, in which there are greater decreases in accessibility as distance increases. Therefore, it is less sensitive to the variations in the other terms of the expression, namely w_j .

To sum it up, both Figures 8 and 9 reveal differences in the levels of accessibility to public employment services. The detected LL clusters are specially worrying, even more so if these are coincidental with HH clusters of unemployed people or unemployment rates. It is for this reason that, on the basis of the research carried out, it is deemed more adequate to use an accessibility measure based on exponential expressions and take into account the size of the employment office catchment area. Unemployed have to queue at some employment offices due to the high number of unemployed people and, consequently, office performance gets compromised, especially in high-unemployment municipalities with low accessibility. Furthermore, most companies use Internet Self Service Solutions. Physical presence is still necessary for the unemployed, especially when they request job mediation, counseling and training.

Figure 8. LISA (local indicators of spatial association) map for index A_i^{Ia} (0.1 and 0.25) and A_i^{IIa} (0.1 and 0.25)

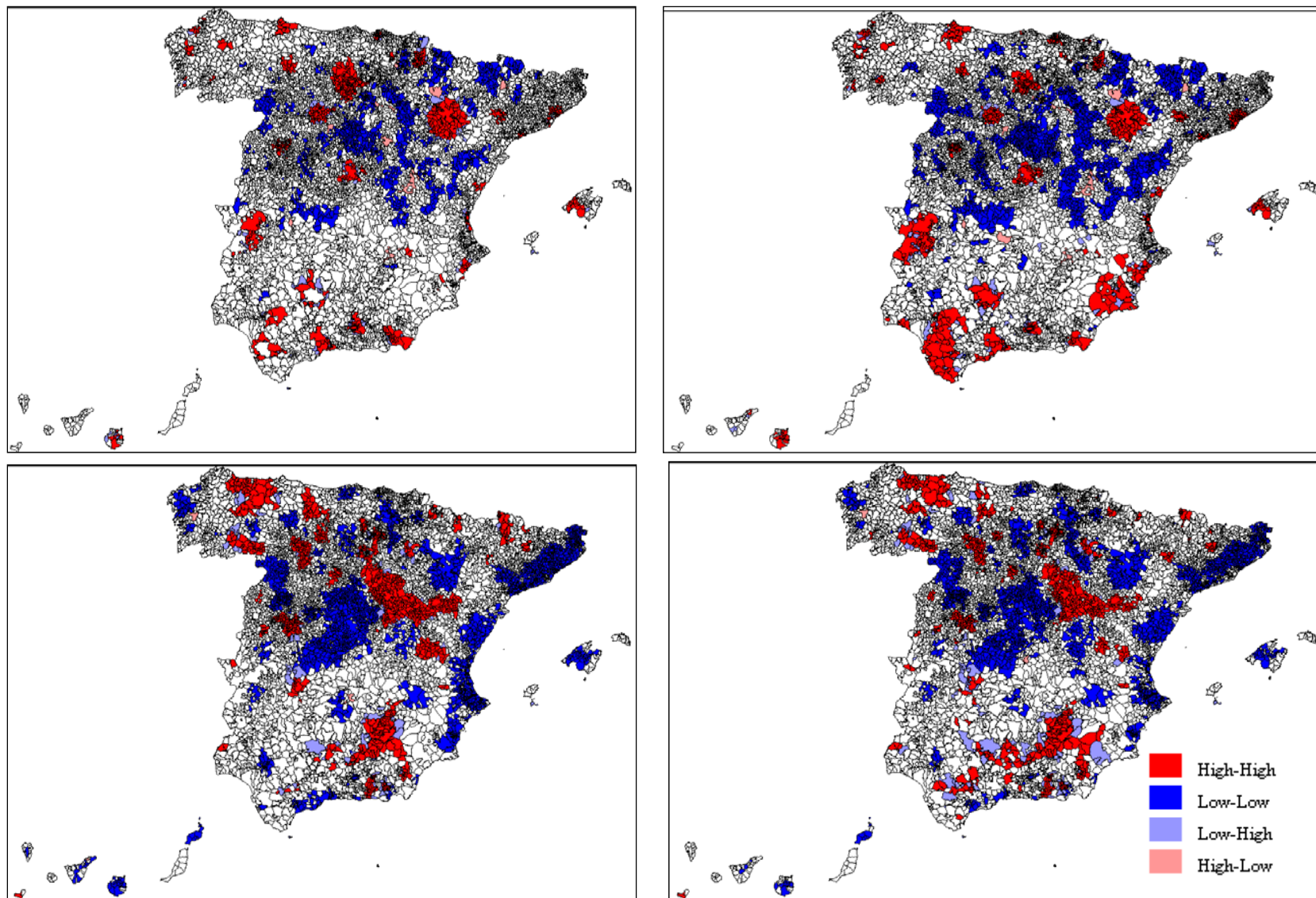
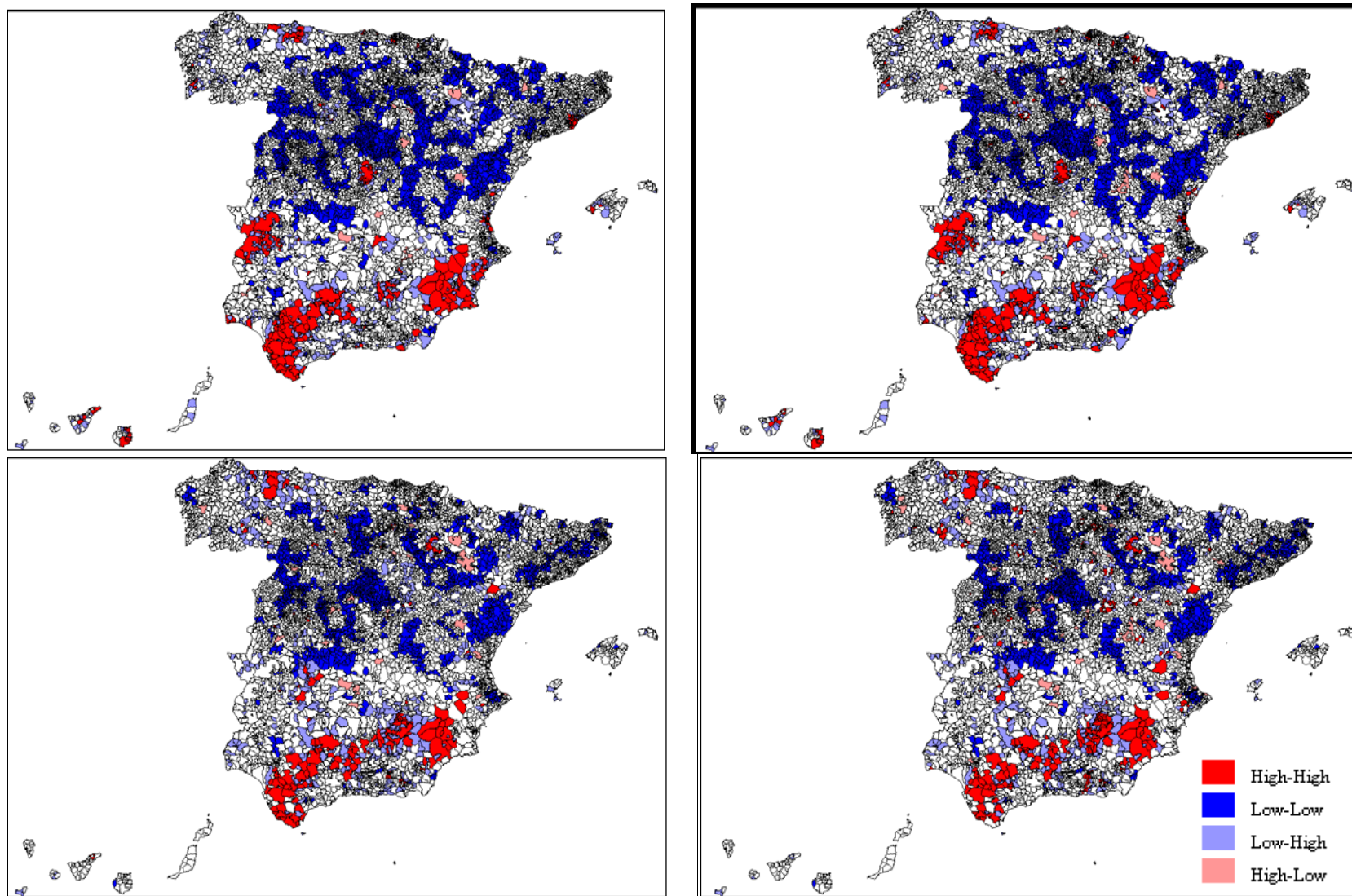


Figure 9. LISA (local indicators of spatial association) map for index A_i^{Ib} (2 and 1.5) and A_i^{IIb} (2 and 1.5)



4. Local unemployment rates and access level to employment offices

4.1. Theoretical framework

Finally, we will consider in this section whether the accessibility to placement offices has effect on local unemployment rates. Even though it is a highly de-aggregated level and data are obtained only with difficulty, employment offices operate at local level. Hence that level is the most adequate for our analysis.

Recent studies on spatial job search have shown that distance to jobs may reduce the probability of leaving unemployment (e.g. Détang-Dessendre and Gagné, 2009). Ihlanfeldt (1997) asserts that labor market information acquisition is considered a type of investment behaviour. At present, theory suggests that the unemployed will go to placement offices in search of information or demanding job-brokering services when benefits are greater than costs. The unemployed may refuse to go to a placement office because traveling expenses are too costly and, in some cases, they have to queue at the office.

From a political perspective, insofar as the relation between unemployment rates and accessibility to employment offices remain negative, investments in accessibility bettering will be regarded as meaningful. Joassart-Marcelli and Giordano (2006) point out that One-Stops are well positioned to serve the unemployed and that access to them does help to reduce local unemployment rates. In our study, it should be taken into account that the accessibility variable covers the idea that, whenever a job-seeker finds work, the unemployment rate in his municipality of residence is reduced, accessibility levels (w_j) grow in municipalities within the same cluster and, consequently, the performance of the employment services gets improved. When we refer to employment services, we mean not only job-seeking mediation but also career counseling, which allows the identification and development of each individual's talent (2008 INEM-SPEE Annual Report). A comprehensive study on the impact of the accessibility to placement offices on job accessibility is still pending, but that is beyond the scope of this paper.

Regional unemployment differentials have been analyzed theoretically and empirically. Elhorst (2003) has reviewed the papers on regional and labor economics published since 1985. He asserts that "Whichever model is used, [...] they all result in the same reduced form equation of the regional unemployment rate". In this equation, labor supply, labor demand and wage-setting factors are usually used as explanatory variables.

In this paper, the model includes as explanatory variables the percentage of male and female of working-age, foreign population, the educational attainment of the population and two dummy variables one for the municipalities belong to the unemployed HH cluster and the other for the unemployed LL ones. The local accessibility level to placement offices is also included. All the variable related information is in Table 3. The basic specification is:

$$\log(u_i) = \eta \log(A_i^{IIa}) + \beta X_i + e_i$$

where u_i is the unemployment rate of each municipality, A_i^{IIa} is the selected accessibility measure and the X matrix collects the explanatory variables described above.

In previous sections, we have established the existence of spatial dependence in unemployment rates so spatial models must be considered in our specification. Similarly,

Longhi and Nijkamp (2007) show that spatial models improve the forecasting performance of nonspatial models, provided that the data available are not correspondent with a well-define local labor market area.

Table 3. Summary statistics

Variable	Mean	SD	Definition	Data source
Absolute local unemployment rate	0.0877	0.0426975	Unemployed population/Total population of working age(16-64)	INEM-SPEE and Padrón 2009
ILLI	0.0246	0.0283031	% of illiterate	Municipal register 2009
PRI*	0.3241	0.1490044	% of Primary education	Municipal register 2009
SEC	0.3969	0.1383664	% of Secondary education and vocational training	Municipal register 2009
UNI	0.0792	0.0483085	% of University graduates	Municipal register 2009
HH	-	-	Unemployed HH cluster	Own elaboration
LL	-	-	Unemployed LL cluster	Own elaboration
A_i^{IIa} with $\lambda=-0.10$	0.1558	0.2043911	Accessibility measure	Own elaboration
A_i^{IIa} with $\lambda=-0.25$	0.0884	0.1484501	Accessibility measure	Own elaboration
FLF	0.5713	0.1037997	Female population (16-64)/ Total female population	Municipal register 2009
MLF	0.6447	0.0739879	Male population (16-64)/ Total male population	Municipal register 2009
FOR	0.0885	0.0931089	Foreign population (16-64)/Total population of working age (16-64)	Municipal register 2009

*The percentage of population with incomplete primary education has been omitted so as to avoid multicollinearity

4.2. Empirical model

Firstly, the model has been estimated by means of OLS. Both local unemployment rates and the accessibility measures have been considered in logarithmic form but it should be stressed that there is not big difference when these variables are used in levels. All the coefficients have the expected signs according to previously theoretical and empirical studies and are statistically significant.

The effect of the accessibility to placement offices is significant and negative (-0.062 Model I and -0.026 Model II). In Model I, the unemployment rate decreases by 0.062% when the accessibility rises 1%. This estimated elasticity diminishes when the accessibility measure A_i^{IIa} with $\lambda = -0.25$ is included in the model.

Standard tests have been carried out so as to assess the adequacy of the regressions. The Breusch-Pagan test for homoskedasticity of the error terms points to heteroskedascity which

in turn is related to the different sizes of the municipalities considered. Table 4 presents the estimation results by means of weighted least squares (WLS). The heteroskedasticity problem persists but with a lower value of the Breuch-Pagan statistic⁸. In any case, since spatial dependences may cause this heteroscedasticity (McMillen, 1992), the result has been interpreted with caution. Similarly, Anselin and Bera (1998) asserted, “every type of spatially dependent error process induces heteroskedasticity as well as spatially autocorrelated errors, which will greatly complicate specification testing in practice”.

We note also that the Kolmogorov-Smirnov⁹ test rejects the assumption of normality of the residuals in models II, III and IV. The WLS estimations obtained are shown in columns 3 and 4 of Table 4 and all the coefficients are significant with the exception of percentage of male of working age (MLF) and percentage of illiterate (ILLI). The effect of the percentage of male in working age is negative but insignificant. Furthermore, we can conclude that the effect of percentage of female of working age (FLF) is higher than the male¹⁰.

Table 4. Estimation Results (local unemployment rate)

	Model I	Model II	Model III	Model IV
	OLS-White	OLS-White	OLS-WLS	OLS-WLS
Intercept	-2.947 (0.062)***	-2.939 (0.062)***	-3.515 (0.083)***	-3.562 (0.084)***
A_i^{IIa} with $\lambda = -0.10$	-0.062 (0.006)***	-	-0.084 (0.005)***	-
A_i^{IIa} with $\lambda = -0.25$	-	-0.026 (0.005)***	-	-0.012 (0.004)***
FLF	1.067 (0.114)***	1.148 (0.115)***	2.112 (0.149)***	2.382 (0.152)***
MLF	-0.295 (0.092)**	-0.293 (0.092)**	-0.122 (0.187)	-0.127 (0.191)
HH	0.333 (0.025)***	0.350 (0.025)***	0.067 (0.006)***	0.085 (0.006)***
LL	-0.278 (0.015)***	-0.291 (0.015)***	-0.264 (0.006)***	-0.291 (0.025)***
ILLI	4.571 (0.232)***	4.549 (0.234)***	4.077 (0.229)***	4.069 (0.234)***
PRI	-0.126 (0.046)**	-0.128 (0.046)**	0.0317 (0.069)	0.056 (0.071)
SEC	-0.127 (0.055)**	-0.100 (0.056)	-0.206 (0.064)***	-0.116 (0.066)*
UNI	-2.070 (0.134)***	-2.023 (0.134)***	-1.396 (0.066)***	-1.260 (0.067)***
FOR	-0.176 (0.060)***	-0.141 (0.060)**	-0.765 (0.029)***	-0.691 (0.030)***
Breusch-Pagan test for heteroskedasticity	614.61***	563.12***	3.85**	27.03***
Kolmogorov-Smirnov	0.2073***	0.2076***	0.2658***	0.263***
R^2 (adj.)	0.271	0.262	0.386	0.360
Number of observations	7,754	7,754	7,754	7,754
Log-likelihood	-5,164.954	-5,211.458	110.447	-48.638
AIC	10,351.91	10,444.92	-198.895	119.276
SBC	10,428.42	10,521.43	-122.379	195.792

⁸ Total population of each municipality is included as weight.

⁹ The Kolmogorov-Smirnov, Cramer-vol Mises, and Anderson-Darling tests are recommended when N is large.

¹⁰ The same conclusion is founded by Cracolici et al. (2007) at the provincial level in Italy.

Another issue is whether the accessibility variable is endogenous. Wooldridge's score test (1995) has been carried out so as to check the endogeneity of the accessibility variable. This test is more appropriate when the residuals show heteroskedasticity. In this test, the instruments are geographic (municipality surface) and demographic characteristics. In this case, the endogenous regressors are actually exogenous. Hence, the OLS estimator is more efficient¹¹.

Moran's I is widely used to detect spatial dependences based on OLS residuals. Here it has been applied to both un-weighted and weighted residuals so that heteroskedasticity may be accounted for. The resulting statistic standard deviation is 37.776 with the un-weighted residuals and 50.252 with the weighted ones. Here, we use a rook contiguity matrix that is row-standardized such that $w_{ij}^s = w_{ij} / \sum_j w_{ij}$ when $i \neq j$ and $w_{ij}^s = 0$ when $i = j$.

At this point, we could consider that the accessibility related variable fully tackles the spatial dependences in the dependent variable, as Martin and Grasjö (2009) show in their study. We should also bear in mind that the accessibility measure in this paper only covers some of the spatial interactions in the local labor market, viz. those related to the activity of public employment services. Other type of spatial interactions (accessibility to jobs and/or firms) are not covered by the measure.

Once the spatial autocorrelation has been detected, we may proceed to incorporate them into the proposed model. In spatial econometrics, the spatial autocorrelation is modeled by means of the relation between the dependent variable Y or the error term and its associated spatial lag, Wy for a spatially lagged dependent variable (spatial lag model) and We for the spatially lagged error term (spatial error model) respectively. The general form for the spatial lag model is:

$$\log(u_i) = \eta \log(A_i^{la}) + \rho W \log(u_i) + \beta X_i + \varepsilon_i; \quad \varepsilon_i \sim N(0, \sigma_\varepsilon^2 I)$$

where $W \log(u_i)$ is the spatially lagged dependent variable for weight matrix W , ρ is the spatial autoregressive parameter, η is the accessibility coefficient and β is a vector of regression parameters.

Spatial autocorrelation can also be incorporated into the model by specifying a spatial error process for the disturbance terms (spatial error model). The most common specification is a spatial autoregressive error process in the error terms:

$$\begin{aligned} \log(u) &= \eta \log(A^{la}) + \beta X + e \\ e &= \theta W e + \varepsilon; \quad \varepsilon_i \sim N(0, \sigma_\varepsilon^2 I) \end{aligned}$$

where θ is the spatial autoregressive coefficient for the error lag We .

Only a few papers deal with the way to specify a spatial econometric model (see Mur and Angulo, 2009). Then, the problem is how to best identify the structure of the underlying spatial dependencies in a given data set. This paper relies on widely used strategic (specific to general) which is based on the LM (Lagrange Multiplier) test and its robust version for local misspecifications (Anselin et al., 1996).

¹¹ Unless an instrumental variables estimator is really needed, OLS should be used instead. In this case, the robust regression statistic is 1.295 with a p-value 0.255.

In the classical approach the LMERR (Lagrange Multiplier for error dependence) and the LMLAG (Lagrange Multiplier for spatially lagged dependent variable) test are compared. If the LMERR is lower than the LMLAG, the spatial lag model should be specified. If not, the spatial error model is to be specified. Florax et al. (2003) have developed a hybrid approach based on the robust version of these tests. Mur and Angulo (2009), however, point out that the robust and the classical approaches render identical results.

These tests are compute on the OLS residuals of the previously estimated models and we consider different criteria to build the spatial weight matrices in order to analyze the sensitivity of the results. For the structure of the spatial effects, there are generally three criteria for creating a spatial weight matrix: contiguity, k-nearest and distance. Firstly, we define a rook contiguity matrix where $w_{ij}=1$ if municipalities i and j share a common edge and $w_{ij}=0$ otherwise. Secondly, k-nearest neighbors' criterion is applied ($k= 3, 4$ y 5) and finally, we obtained distance-based matrix where $w_{ij}=1$ if the distance between i and j is less than d_{ij} and $w_{ij}=0$ if $i \neq j$ or $d > d_{ij}$ ($d=20, 30$ and 40 km). The value of the test statistics are collected in Table 5 and the p-value is only included if it is higher than 0.01.

Table 5: Spatial dependence statistics by alternative spatial weight matrices

	Wq	WK3	WK4	WK5	W20	W30	W40
LMERR	1417.684	1169.113	1427.895	1695.625	3635.279	5616.056	7286.241
LMLAG	1928.702	1430.668	1829.884	2260.817	3959.976	4611.282	4607.672
RLMERR	3.505	11.202	0.1946(0.695)	3.013(0.082)	337.587	1687.032	3357.163
RLMLAG	514.343	272.750	402.185	568.205	4297.563	682.257	678.594
SARMA	1932.307	1441.869	1830.079	2263.831	519.051	6298.313	7964.835

We can observed that, in the case of matrices Wq, WK3, WK4, WK5 and W20, LMLAG>LMERR and the same result is obtained with the robust version of these tests (R-LMLAG and R-LMERR) so the appropriate model would be the spatial lag model. By the contrary, when these tests are computed with W30 y W40 the spatial error model is indicated as more appropriate. However, we are working with municipality data and the consideration of large distance is difficult to justify from an economic point of view. In fact, when these matrices are used we are losing the advantage of working with a high level of spatial disaggregation. As consequence, a spatial lag specification is choosing based on the results of the specification test together with the economic theoretical framework¹². In this sense, LeSage and Pace (2009) assert that spatial lag models have been used in contexts where there is a theoretical motivation for Y to be depend on neighboring values of Y . Molho (1995) and Patacchini and Zenou (2007) have shown theoretical explanation to the spatial correlation between unemployment rates.

Maximum likelihood (ML) is the most conventional estimation method for a standard spatial autoregressive model (SAR) where the error terms are assumed to follow a normal distribution. The computational complexities of the Jacobian term ($|\mathbf{I}-\rho\mathbf{W}|$ in the SAR model and $|\mathbf{I}-\theta\mathbf{W}|$ in the SEM model) represent the main problem of this method. This

¹²These results show up one of the unsolved questions in spatial econometrics: the selection of the spatial weight matrix (Fernández et al. 2009).

computational problem is sorted out by means of the simplification solution proposed by Ord (1975) or the approximation option developed by Smirnov and Anselin (1996).

The use of the spatially lagged dependent variable Wy as explanatory variable may be understood as a form of endogeneity or simultaneity leading to the instrumental variable approach (IV)/two stage least squares (2SLS). Anselin (1988) considers this method more appropriate when the error terms are not normally distributed but some recent studies point out the inefficiency problem in the 2SLS estimators (2SLS) compared to the maximum-likelihood estimator (MLE). Furthermore, it will be inconsistent (2SLS) if the exogenous regressors are irrelevant (Lin and Lee, 2010).

The Generalized Moment Estimator (GMME) for the autoregressive parameter in a spatial model, proposed by Kelejian and Prucha (1999), also allows us to solve the problems previously described. They prove that the GM estimator is consistent without the assumption of normality. Recently, Lin and Lee (2010) have shown the robustness of the GMM estimators under unknown heteroskedasticity —a context in which the maximum likelihood estimator is usually inconsistent.

The local unemployment rate equation is estimated by means of ML, 2SLS and GMM methods and the results are shown in Table 6. We consider some spatial weight matrices based on geographic contiguity (municipalities sharing bounding points are neighbourhoods) or on the distance between municipalities but we only present the results obtained with a k-nearest neighbour matrix $k=5$.

As we can see, the results are qualitative similar in general terms among the methods and they are quantitative the same when 2SLS and GMM are compared. The first column in Table 6 shows the estimation results of model by ML. The coefficient of the spatial lag term is 0.54 and is highly significant. The LR test on the spatial autoregressive coefficient is highly significant but according to the LM test for residual autocorrelation, uncontrolled spatial effects remain in the residuals. Furthermore, a spatial Hausman test has been applied in order to detect the presence of omitted variables. In this case, we reject the null hypothesis¹³ (statistic value=522.52***) and as consequence a model with a spatial lag of the dependent variable is more plausible than a spatial error model.

Based on the various result, we see that the unemployment rate in the Spanish municipalities exhibits a strong spatial autocorrelation, with an estimated spatial coefficient of around 0.78-0.83. Thus, about 78% (2SLS) - 83% (GMM) of the changes in the unemployment rates of neighbouring municipalities will be absorbed by a municipality's own unemployment rate. The estimated spatial coefficient is 0.54 when the model is estimated by ML. One explanation for this smaller value could be the non-normality of the error term together with the heteroskedasticity problem¹⁴ so the 2SLS and GMM are more adequate.

¹³ The Hausman test statistic follows a chi-squared distribution with degrees of freedom equal to the number of explanatory variables.

¹⁴ Lin and Lee (2010) show that MLE estimator is generally inconsistent with unknown heteroskedasticity if the SAR model were estimated as if the disturbances were i.i.d.

Table 6. Estimation Results (local unemployment rate) for Spatial Models

	ML	2SLS	GMM	GMM-HETEROS
Intercept	-1.4273 (0.048)***	-0.7866 (0.104)***	-0.6266 (0.094)***	-0.4339 (0.068)***
A_i^{IIa} with $\lambda = -0.10$	-0.0279 (0.005)***	-0.0142 (0.005)**	-0.009 (0.0045)**	-0.006 (0.003)**
FLF	0.5395 (0.057)***	0.3441 (0.069)***	0.2744 (0.070)***	0.223 (0.046)***
MLF	-----	----	-----	---
HH	0.1867 (0.021)***	0.10548 (0.023)***	0.0904 (0.023)***	0.0729 (0.011)***
LL	-0.1243 (0.013)***	-----	-----	-0.0535 (0.014)***
ILLI	2.5954 (0.184)***	1.4919 (0.237)***	1.2505 (0.228)***	0.6756 (0.167)***
PRI	-----	-----	-----	
SEC	-----	0.1078 (0.044)**	0.1150 (0.044)***	
UNI	-1.3766 (0.114)***	-1.0521 (0.119)***	-0.9873 (0.118)***	-0.6419 (0.082)***
FOR	-----	-----	-0.0874 (0.052)*	
ρ	0.5451 (0.012)***	0.7856 (0.029)***	0.8318 (0.027)***	0.8712 (0.022)***
LRrho	1686.3***			
Lambda				-0.6677 (0.024)***
Wald				50.726***
Heteroskedasticity (Breusch-Pagan)	431.7991***	376.9682***	428.5944***	446.1599***
Kolmogorov-Smirnov	0.2418***	0.2375***	0.2061***	0.2302***
R^2	0.4228	0.4636	0.4607	0.4550
LM test for residual autocorrelation	612.79***			
Number of observations	7,754	7,754	7,754	7,754
Sigma^2	0.1676	0.1630	0.1638	0.1658

Note: in the 2SLS model, the spatial lag of the explanatory variables is included as instrumental variables (WX).

In accordance with our hypotheses the unemployment rates appear to be inversely related to the accessibility measure. Its coefficient is significant and negative but is reduce to -0.026(ML), -0.014(2SLS) and -0.009 (GM). If we were analyzing two linear regression models, it could be possible to conclude that the elasticity of accessibility is lower when spatial autocorrelation is included explicitly into the model. But in models containing spatial lag of the dependent variable, the interpretation of the parameters are more complicated. In the spatial lag model, a change in the dependent variable for a single region can affect the dependent variable in all other regions. Thus, a change in one explanatory variable in municipality i will not only exert a direct effect on its unemployment rate, but also an indirect effect on the unemployment rate in other municipalities. As consequence, the impact on the dependent variable in one region due to a change in one of the explanatory variables usually is not equal to its estimated coefficient.

To collect all these interactions among regions, Pace and Lesage (2006) propose new measures to reach a correct interpretation of the spatial models and distinguish between direct and indirect impacts. The direct impact shows the average response of the dependent variable to independent variables including feedback influences that arise as a result of impacts passing

through neighbours and back to the municipality itself¹⁵ and the indirect impact summarizes the effect of the change in one region to the others and how changes in all regions affect one region. In Table 7, we include the estimated direct and indirect impact by means of 2SLS and GMM.

Table 7: Direct, indirect and total impact estimations by means 2SLS/IV and GMM:

Variables	Direct	Indirect	Total
Accessibility	-0.0182 (-2.77)	-0.0481 (-2.85)	-0.0662 (-2.88)
ILLI	1.9127 (7.19)	5.0467 (7.07)	6.9594 (8.05)
SEC	0.1382 (2.41)	0.3646 (2.12)	0.5028 (2.21)
UNI	-1.3489 (-9.49)	-3.5591 (-5.49)	-4.9080 (-6.66)
HH	0.1352 (4.81)	0.3565 (4.38)	0.4917 (4.71)
MLF	0.4413 (5.39)	1.1642 (5.08)	1.6055 (5.48)

Variables	Direct	Indirect	Total
Accessibility	-0.0134 (-1.97)	-0.0455 (-1.98)	-0.0504 (-1.99)
ILLI	1.6977 (6.17)	5.8229 (5.71)	7.5197 (6.28)
SEC	0.1581 (2.51)	0.5551 (2.18)	0.7132 (2.27)
UNI	-1.3455 (-8.73)	-4.6679 (-5.05)	-6.0135 (-5.86)
FOR	0.1231 (1.68)	0.4378 (1.52)	0.5609 (-1.56)
HH	0.1228 (4.21)	0.4229 (3.74)	0.5458 (3.96)
MLF	0.3699 (4.08)	1.2658 (4.07)	1.6358 (4.22)

Note: z-statistics in parentheses based on 2000 simulated draws of the parameters

The accessibility to placement offices has a direct effect slightly higher (and significant) than the coefficient estimate. This difference is due to impacts passing through neighbouring regions and back to the region itself. Consequently, we obtain a positive feedback effect.

Most interesting is the estimation result of the indirect impact. It is significant and five times higher than the coefficient estimate in GMM model (3.5 times higher in 2SLS model) showing a positive influence of the accessibility to the placement offices throughout the spatial dependences among municipalities.

The total impact is -0.0504(GM) and -0.0662(2STLS) and it means if accessibility increases 1%, the unemployment rate decreases 0.0504%/0.0662%.

All coefficients of the independent variables –except MLF, PRI and FOR- are statistically significant (Table 6). In addition, evidence in favour of the hypothesis of the unemployment persistent from a geographical perspective is founded. The coefficient of the dummy variable HH is positive which mean that a municipality belonging to the HH cluster is strongly constrained by this spatial pattern. By the contrary, the variable LL is not significant in 2SLS and GMM models and is significant and negative in the ML estimation meaning that when a municipality is a member of a LL cluster, it is received a positive influence in term of unemployment.

Regarding to the estimation results of the educational variables, the percentage of university graduates is significant and negative whereas the percentage of illiterate and secondary education is positive and significant. The coefficient of the secondary education is lower than the coefficient of the illiterate as we expected.

¹⁵The main diagonal of higher order spatial weight matrices are non-zero allowing to collect these feedback effects.

With these results if the percentage of the secondary education people decreases 1 point in a municipality i to the benefit of the university degree people, the unemployment rate change $-1.3455-(0.1581)=-1.5036$ points in this municipality. As we can describe above, the indirect impact estimates the spatial spillover if it is significant. In this case, the spatial spillover associated to a global improvement of the educational attainment is very important. If the percentage of university degree increase in all municipalities 1 point, the impact on a typical municipality was a reduced of unemployment rate of 4.66 points.

Finally, the residuals of the spatial lag model are analyzed to check if all the spatial autocorrelation was eliminated. The result of the LM test is significant to reject the null hypothesis of no spatial correlation in the residual errors. One option is to estimate a spatial error model with the dependent lagged variable or assign this spatial error autocorrelation to a misspecification problem (omitted systematic variables). In this second option, the Spatial Durbin could be an option because it includes as regressor the spatial lag of the explanatory variables. But, as we explain above, there is a heteroskedasticity problem that suggests the specification of one model which allows controlling this unknown heteroskedasticity in the error term.

As we describe above the GMM estimation is a good option when the normality option is not verify. Recently, Kelejian and Prucha (2007) extended the GMM approach to a spatial autoregressive disturbance process with heteroskedasticity innovations. In this paper, we adopt the extension presented by Arraiz et al. (2010) where it is specified a linear spatial model that allows for spatial lags in the dependent variable, exogenous variables and disturbances and this specification allows for heteroskedasticity of unknown form. The simulation results show that the GMM estimators of the spatial parameters are consistent in the presence of heteroskedasticity innovation whereas quasi-maximum-likelihood estimators are not consistent.

The fourth column in Table 6 shows the estimation results of model by GMM with heteroskedasticity innovations. In this model, we assume that the disturbance process is known to follow a spatial autoregressive process of order one and this is the expression:

$$\log(u)=\eta\log(A^{lla})+\beta X+e$$

$$e =\theta We +\varepsilon;$$

The innovations $\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n$ are assumed independent with zero mean and non-constant variance σ_i^2 .

The estimate coefficient of the accessibility measure is negative and statistically significant and we obtain a strong spatial dependence among municipality unemployment rates with a significant spatial effect.

The presence of heteroskedasticity has no impact on the coefficient estimates of this empirical model when 2SLS and GMM methods are compared. The various approaches are applied to the study of local unemployment rates and we find that accessibility measure helps to reduce it.

5. Conclusions and policy recommendations

We have obtained that there is spatial heterogeneity across the local employment offices. In some autonomous communities the number of placement offices appears to be too small with respect to the unemployed they manage (especially in Madrid, Canary Islands, Community of Valencia and Catalonia). In addition, introducing the size of the employment offices catchment area in the accessibility measures improves the precision with which we measure the level of accessibility between a municipality and its employment office. We have detected the main clusters of low accessibility to employment offices and also relevant clusters with high unemployment in Spain in 2009.

On one side, our results suggest that policy makers seek to improve the accessibility to placement offices in the municipalities with low accessibility to employment offices in order to ensure that all unemployed receive the adequate assistance to find suitable employment. But, on the other side, we also find that accessibility to employment offices has a significant influence in unemployment rate.

Based on the various ML, 2SLS and GMM results, we show a strong spatial correlation between unemployment rates, i.e., the neighbourhood influences are very important in the labor market. This view is consistent with other empirical studies like Molho (1995) or Patacchini and Zenou (2007), so the spatial perspective cannot be ignored in the analysis of the labor market.

As a consequence of the decentralization process in the last 20 years in Spain, the regions are responsible for the active labor market policies and for the creation and/or reorganization of catchment areas. A possible recommendation is to create new employment offices in order to reduce the size of their catchment areas as well as support the communication among them (especially in aspects related to make offers common to all the offices). We recommend the creation of new employment offices so that the size of their catchment areas may be reduced. Support to interoffice collaboration is also recommended, especially when it may lead to higher diffusion of job openings. However, we need to learn more about the efficacy of the several types of services that every employment office offers.

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