THE ACCESSIBILITY TO EMPLOYMENT OFFICES IN THE SPANISH LABOR MARKET

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RESUMEN: This paper focuses on the differences in the levels of accessibility to public employment offices in Spain. We use administrative 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 and test whether a higher accessibility to employment offices could contribute to reduce local unemployment rates. We also find different levels of accessibility to employment offices across the national territory and propose improvements in the PES performance. Our results reveals that public employment offices are insufficient in number and/or poorly located.

PALABRAS CLAVE: Keywords: employment offices, unemployment, accessibility, spatial econometrics.

JEL: J68, J60, C21, R12.
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 job-seekers—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 ALMPs. 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 population profile.

With respect to the PES, in theory it provides job-seekers 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 workers 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

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1 The devolution of this power to the Basque regional government will put an end to this decentralization process.
local level and, as in other countries (Fertig et al., 2006), we do not know how public funding is distributed among the offices. 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 an employment office catchment area so that any difference in access may be adequately tackled. 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 the 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).

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 number of unemployed people would still be extremely important, since it constitutes a natural limit to the performance of any employment office. Figure 1 displays the 2009 average of unemployment rates by municipality. 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.

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.

3 The local unemployment rate is estimated as the total number of unemployed people in the municipality over the total working age population.
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.

The box map\(^4\) below (Figure 2) 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.

\(^{4}\) 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).
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 3 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).
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) and Los Realejos (Tenerife).

Figure 4 shows the existence of steep differences between the Spanish autonomous communities in the number of unemployed workers per employment office. Spain is made up of 2 autonomous cities —Ceuta and Melilla— and 17 autonomous communities, each with its own heritage, government and PES. The number of employment offices seems to be

<table>
<thead>
<tr>
<th>Number of municipalities</th>
<th>Employment offices</th>
</tr>
</thead>
<tbody>
<tr>
<td>7524</td>
<td>0</td>
</tr>
<tr>
<td>526</td>
<td>1</td>
</tr>
<tr>
<td>35</td>
<td>2</td>
</tr>
<tr>
<td>10</td>
<td>3</td>
</tr>
<tr>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>1</td>
<td>11</td>
</tr>
<tr>
<td>1</td>
<td>19</td>
</tr>
<tr>
<td>Total: 8109</td>
<td>Total: 718</td>
</tr>
</tbody>
</table>
far below the number of jobless they have to attend to, especially in Madrid, the Canary Islands, the Valencian Community and Catalonia, so differences in accessibility may be expected.

**Figure 4. Average number of unemployed workers per placement office. NUTS-1 (2009)**

![Graph showing average number of unemployed workers per placement office.]

### 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 Gaigné (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.

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5 Joassart-Marcelli and Stephens (2009) analyze the immigrants’ spatial accessibility to financial institutions in Greater Boston.
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. 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. In other words, every unemployed worker should be equally treated, no matter where they may live. For us, 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) 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 job-seeker accessibility to employment offices consists in counting the existing employment offices within a given area. As we explained above, Figure 3 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 unemployed assigned to an employment office —i.e. by adding up the number of jobless in the municipalities serviced by a given employment office. In the case of Spain, every unemployed worker is assigned an employment office by the National Employment Authority depending on their place of residence. 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.

Next, we will consider two more types of accessibility measures (also known as 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 unemployed within each employment office catchment area. We would like to have had

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6 Talen and Anselin (1998) utilize a case-study on the location of playgrounds in order to analyze the spatial equity in Tulsa.
access to the number of job counselors and/or counseling sessions per unemployed worker, but access to this information is not provided at local level. The first type of measure (denoted by the superscript ‘I’) 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.

\[
A_{ij}^{la} = EO_j \left( e^{-\lambda d_{ij}} \right)
\]

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, \( \lambda \) 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 \( \lambda = -0.25 \). 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 to the office when job-seekers 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.

\[
A_{ij}^{lb} = \frac{EO_j}{d_{ij}^\alpha}
\]

In this case, \( \alpha \) is a parameter of the distance-decay function. The higher the value of the parameter, the greater will be the resulting differential between near and distant municipalities. This value crucially depends on the type of activity involved (Holl, 2007).

\footnote{Joassart-Marcelli and Giordano (2006) establishes \( \lambda = -0.25 \).}
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 1.5\(^8\).

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.

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

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

Where \(A_i\) is the municipality accessibility, \(w_j\) is the number of employment offices (\(EO_j\)) per employment office catchment area (\(\sum_{i} u_i\)), measured as the number of unemployed workers 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 \(\lambda\) is a parameter of the distance-decay function. The possible range of values to which that parameter may be set was established above.

Similarly, the index \(A_i^{\text{IIb}}\) 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.

\[
A_i^{\text{IIb}} = \frac{\sum_{j} EO_j}{\sum_{i} u_i} / d_{ij}^{\alpha} \rightarrow A_i^{\text{IIb}} = \left[ w_j / d_{ij}^{\alpha} \right] \tag{4}
\]

Again, \(\alpha\) is a parameter of the distance-decay function and adopts the values set before.

According to these measures, an employment office located 15 kilometers away will provide a greater contribution to the accessibility index value than one located 30 kilometers away.

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

\(^8\) Bruinsma and Rietveld (1993), Gutierrez (2001) and Holl (2007) assume \(\alpha = 1\) in their respective analyses of the accessibility to economic activity.
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. Tsou et al. (2005) also recommend 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). Furthermore, 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 workers 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 local 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 local 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 so that none is scattered randomly or independently in space.
Table 2. Measure of global spatial autocorrelation (Moran’s I)

<table>
<thead>
<tr>
<th>Variables</th>
<th>I</th>
<th>Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployed people</td>
<td>0.147</td>
<td>24.334</td>
</tr>
<tr>
<td>Local unemployment rate</td>
<td>0.574</td>
<td>85.300</td>
</tr>
<tr>
<td>Employment offices*</td>
<td>0.119</td>
<td>18.214</td>
</tr>
<tr>
<td>( A_{i1} ) (( \lambda = 0.1 ))</td>
<td>0.618</td>
<td>91.427</td>
</tr>
<tr>
<td>( A_{i1} ) (( \lambda = 0.25 ))</td>
<td>0.505</td>
<td>75.891</td>
</tr>
<tr>
<td>( A_{i2} ) (( \lambda = 0.1 ))</td>
<td>0.625</td>
<td>92.272</td>
</tr>
<tr>
<td>( A_{i2} ) (( \lambda = 0.25 ))</td>
<td>0.624</td>
<td>91.711</td>
</tr>
<tr>
<td>( A_{i3} ) (( \alpha = 2 ))</td>
<td>0.142</td>
<td>21.562</td>
</tr>
<tr>
<td>( A_{i3} ) (( \alpha = 1.5 ))</td>
<td>0.165</td>
<td>25.126</td>
</tr>
<tr>
<td>( A_{i4} ) (( \alpha = 2 ))</td>
<td>0.057</td>
<td>8.891</td>
</tr>
<tr>
<td>( A_{i4} ) (( \alpha = 1.5 ))</td>
<td>0.076</td>
<td>11.738</td>
</tr>
</tbody>
</table>

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

3.1. 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:

\[
I_i = \frac{\sum z_i \sum w_{ij} z_j}{\sum z_i^2 / n + \sum_j w_{ij} z_j; \quad z_i = x_i - \bar{x} }
\]

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 municipality and its neighbors.

Figure 5 shows the LISA map for unemployed people in Spain for 2009. The figure suggests that high unemployment municipalities tend to be close to other high unemployment municipalities. 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 local 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.

As regards the LISA map for 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.
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 workers and test whether the employment offices are located in municipalities where there is 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 also 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 are good in terms of equity, for it ensures the existence of an employment office near 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 workers and employment offices. Employment offices are located around municipalities with high numbers of jobless. This distribution may be deemed efficient, 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 office accessibility.
3.3. Results based on the comparison of accessibility indices

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 surrounding municipalities, 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 jobless from the city itself and the surrounding municipalities, who also have to travel to the offices. Therefore, the relation \( w \) is very low in these municipalities.

Figure 9 shows the LISA maps for the accessibility indices \( A^{Ib}_i \) (upper half of the page) and \( A^{IIb}_i \) (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 \( A^{Ib}_i \) 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 \( A^{Ia}_i \) and, therefore, with those in Figures 5 and 7. In the case of the accessibility index \( A^{IIb}_i \), its spatial pattern does not differ greatly from that of the index \( A^{Ib}_i \).

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 \( A^{IIb}_i \) and the \( A^{Ib}_i \) 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 \( w \).

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 especially worrying, even more so if these are coincidental with HH clusters of unemployed people or local 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 in order to include a competition factor. Job-seekers 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. However, 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) maps for indices $A_{iA}^{Ia}$ (0.1 and 0.25) and $A_{iA}^{IIa}$ (0.1 and 0.25)
Figure 9. LISA (local indicators of spatial association) map for indices $A_{12}^{I_{b}}$ (2 and 1.5) and $A_{12}^{II_{b}}$ (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 employment 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 likelihood of leaving unemployment (e.g. Détang-Dessendre and Gaigné, 2009). Ihlanfeldt (1997) asserts that labor market information acquisition is considered a type of investment behavior. At present, theory suggests that the unemployed will go to placement offices in search of information or 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 their municipality of residence is reduced, accessibility levels \(w_j\) grow in municipalities within the same cluster or regional labor office 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. The model in this paper includes as explanatory variables the rates of foreign population and males and females of working-age, the educational attainment of the population and two dummy variables, one for municipalities within HH clusters and the other for municipalities within 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:

\[
\log(u_i) = \eta \log(A_{iua}) + \beta X_i + \epsilon_i
\]

where \(u_i\) is the unemployment rate of each municipality, \(A_{iua}\) 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\textsuperscript{9}.

\begin{table}[h]
\centering
\caption{Summary statistics}
\begin{tabular}{|l|l|l|l|l|}
\hline
Variable & Mean & SD & Definition & Data source \\
\hline
Local unemployment rate & 0.0877 & 0.0426975 & Unemployed population / Total population of working age (16-64) & INEM-SPEE and 2009 Census \\
ILLI & 0.0246 & 0.0283031 & % Illiteracy & 2009 Municipal census \\
PRI & 0.3241 & 0.1490044 & % Primary education & 2009 Municipal census \\
SEC & 0.3969 & 0.1383664 & % Secondary education or vocational training & 2009 Municipal census \\
UNI & 0.0792 & 0.0483085 & % Higher education & 2009 Municipal census \\
HH & - & - & HH cluster & Own elaboration \\
LL & - & - & LL cluster & Own elaboration \\
A\textsubscript{IIa} with \(\lambda=-0.10\) & 0.1558 & 0.2043911 & Accessibility measure & Own elaboration \\
A\textsubscript{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 & 2009 Municipal census \\
MLF & 0.6447 & 0.0739879 & Male population 16-64 / Total male population & 2009 Municipal census \\
FOR & 0.0885 & 0.0931089 & Foreign population (16-64) / Total population of working age (16-64) & 2009 Municipal census \\
\hline
\end{tabular}
\end{table}

\*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 accessibility measures have been considered in logarithmic form, but it should be stressed that the use of these variables in levels makes no considerable difference. The coefficients’ signs are as expected and in accordance with previous theoretical and empirical studies. Also, they 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 accessibility rises by 1\%. This estimated elasticity diminishes when the accessibility measure \(A\textsubscript{IIa}\) 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 heteroskedasticity, 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 the value of the Breuch-Pagan statistic is lower\textsuperscript{10}. In any case, since spatial dependences may cause this heteroskedasticity

\textsuperscript{9} 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-defined local labor market area.

\textsuperscript{10} The total population of each municipality is included as weight.
(McMillen, 1992), the result has been interpreted with caution. Similarly, Anselin and Bera (1998) assert that «every type of spatially dependent error process induces heteroskedasticity as well as spatially autocorrelated errors, which will greatly complicate specification testing in practice».

We may also note that the Kolmogorov-Smirnov\(^\text{11}\) test has led us to reject 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. With the exception of the percentages of males of working age (MLF) and illiterates (ILLI), all the coefficients are significant. The effect of the percentage of males of working age is negative but insignificant. Additionally, we may conclude that the effect of the percentage of females of working age (FLF) is higher than that of the males\(^\text{12}\).

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, whose instruments are geographic (municipality surface) and demographic characteristics, is more appropriate when the residuals show heteroskedasticity. In this case, the endogenous regressors are actually exogenous. Hence the OLS estimator is more efficient\(^\text{13}\).

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

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 within local labor markets, viz. those related to the activity of public employment services. Other types of spatial interactions (accessibility to jobs and/or firms) are not covered by the measure.

---

\(^{11}\) The Kolmogorov-Smirnov, Cramer-von Mises and Anderson-Darling tests are recommended when \(N\) is large.

\(^{12}\) Cracolici et al. (2007) reach the same conclusion for the Italian provinces.

\(^{13}\) 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.
Table 4. Estimation results (local unemployment rate)

<table>
<thead>
<tr>
<th></th>
<th>Model I</th>
<th>Model II</th>
<th>Model III</th>
<th>Model IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS-White</td>
<td>OLS-White</td>
<td>OLS-WLS</td>
<td>OLS-WLS</td>
</tr>
<tr>
<td>Intercept</td>
<td>-2.947 (0.062)***</td>
<td>-2.939 (0.062)***</td>
<td>-3.515 (0.083)***</td>
<td>-3.562 (0.084)***</td>
</tr>
<tr>
<td>(A_{\text{IIa}} ) with ( \lambda = -0.10 )</td>
<td>-0.062 (0.006)***</td>
<td>-0.084 (0.005)***</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>IIa</td>
<td>-0.10</td>
<td>-0.062 (0.005)***</td>
<td>-0.012 (0.004)***</td>
<td>-</td>
</tr>
<tr>
<td>FLF</td>
<td>1.067 (0.114)***</td>
<td>1.148 (0.115)***</td>
<td>2.112 (0.149)***</td>
<td>2.382 (0.152)***</td>
</tr>
<tr>
<td>MLF</td>
<td>-0.295 (0.092)**</td>
<td>-0.293 (0.092)**</td>
<td>-0.122 (0.187)</td>
<td>-0.127 (0.191)</td>
</tr>
<tr>
<td>HH</td>
<td>0.333 (0.025)***</td>
<td>0.350 (0.025)***</td>
<td>0.067 (0.006)***</td>
<td>0.085 (0.006)***</td>
</tr>
<tr>
<td>LL</td>
<td>-0.278 (0.015)***</td>
<td>-0.291 (0.015)***</td>
<td>-0.264 (0.006)***</td>
<td>-0.291 (0.025)***</td>
</tr>
<tr>
<td>ILLI</td>
<td>4.571 (0.232)***</td>
<td>4.549 (0.234)***</td>
<td>4.077 (0.229)***</td>
<td>4.069 (0.234)***</td>
</tr>
<tr>
<td>PRI</td>
<td>-0.126 (0.046)**</td>
<td>-0.128 (0.046)**</td>
<td>0.0317 (0.069)</td>
<td>0.056 (0.071)</td>
</tr>
<tr>
<td>SEC</td>
<td>-0.127 (0.035)**</td>
<td>-0.100 (0.056)</td>
<td>-0.206 (0.064)***</td>
<td>-0.116 (0.066)***</td>
</tr>
<tr>
<td>UNI</td>
<td>-2.070 (0.134)***</td>
<td>-2.023 (0.134)***</td>
<td>-1.396 (0.066)***</td>
<td>-1.260 (0.067)***</td>
</tr>
<tr>
<td>FOR</td>
<td>-0.176 (0.060)***</td>
<td>-0.141 (0.060)***</td>
<td>-0.765 (0.029)***</td>
<td>-0.691 (0.030)***</td>
</tr>
<tr>
<td>Breusch-Pagan test for heteroskedasticity</td>
<td>614.61***</td>
<td>563.12***</td>
<td>3.85**</td>
<td>27.03***</td>
</tr>
<tr>
<td>Kolmogorov-Smirnov</td>
<td>0.207***</td>
<td>0.267***</td>
<td>0.2658***</td>
<td>0.263***</td>
</tr>
<tr>
<td>( R^2 ) (adj.)</td>
<td>0.271</td>
<td>0.262</td>
<td>0.386</td>
<td>0.360</td>
</tr>
<tr>
<td>Number of observations</td>
<td>7,754</td>
<td>7,754</td>
<td>7,754</td>
<td>7,754</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-5,164.954</td>
<td>-5,211.458</td>
<td>110.447</td>
<td>-48.638</td>
</tr>
<tr>
<td>AIC</td>
<td>10,351.91</td>
<td>10,444.92</td>
<td>-198.895</td>
<td>119.276</td>
</tr>
<tr>
<td>SBC</td>
<td>10,428.42</td>
<td>10,521.43</td>
<td>-122.379</td>
<td>195.792</td>
</tr>
</tbody>
</table>

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

\[
\log(u) = \eta \log(A^{lu}) + \rho W \log(u) + \beta X + \varepsilon; \quad \varepsilon \sim N(0, \sigma^2 \mathbf{I})
\]  

where \( W \log(u) \) is the spatially lagged dependent variable for the weight matrix \( W \), \( \rho \) is the spatial autoregressive parameter, \( \eta \) is the accessibility coefficient and \( \beta \) 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:

\[
\log(u) = \eta \log(A^{lu}) + \beta X + \varepsilon \quad e = \theta W e + \varepsilon; \quad \varepsilon \sim N(0, \sigma^2 \mathbf{I})
\]  

where \( \theta \) is the spatial autoregressive coefficient for the error lag \( W e \).
Only a few papers deal with how 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 dependences in a given data set. This paper relies on widely used strategy (specific to general), which is based on the LM (Lagrange Multiplier) test and its robust version for local misspecifications (Anselin et al., 1996).

In the classical approach, the LMERR (Lagrange Multiplier for error dependence) and the LMLAG (Lagrange Multiplier for spatially lagged dependent variable) 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 have been computed on OLS residuals of the previously estimated models. We have also considered different criteria to build the spatial weight matrices that allowed us to analyze the sensitivity of the results. As regards the structure of the spatial effects, three criteria are usually considered in the creation of 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, we apply a k-nearest neighbors’ criterion \((k = 3, 4, 5)\). Then, we obtain a 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 \( d_{ij} > d_{ij} \) \((d = 20, 30 \text{ and } 40 \text{ km})\). Table 5 shows the values of the test statistics. The p-value is included only if it is greater than 0.01.

Table 5: Spatial dependence statistics by alternative spatial weight matrices

<table>
<thead>
<tr>
<th></th>
<th>Wq</th>
<th>WK3</th>
<th>WK4</th>
<th>WK5</th>
<th>W20</th>
<th>W30</th>
<th>W40</th>
</tr>
</thead>
<tbody>
<tr>
<td>LMERR</td>
<td>1417.684</td>
<td>1169.113</td>
<td>1427.895</td>
<td>1695.625</td>
<td>3635.279</td>
<td>5616.056</td>
<td>7286.241</td>
</tr>
<tr>
<td>LMLAG</td>
<td>1928.702</td>
<td>1430.668</td>
<td>1829.884</td>
<td>2260.817</td>
<td>3959.976</td>
<td>4611.282</td>
<td>4607.672</td>
</tr>
<tr>
<td>RLMERR</td>
<td>3.505</td>
<td>11.202</td>
<td>0.1946</td>
<td>0.082</td>
<td>3.013</td>
<td>0.695</td>
<td>3.013</td>
</tr>
<tr>
<td>RLMLAG</td>
<td>514.343</td>
<td>272.750</td>
<td>402.185</td>
<td>4297.563</td>
<td>1678.032</td>
<td>3357.165</td>
<td></td>
</tr>
<tr>
<td>SARMA</td>
<td>1932.307</td>
<td>1441.869</td>
<td>1830.079</td>
<td>2263.831</td>
<td>519.051</td>
<td>6298.313</td>
<td>7964.835</td>
</tr>
</tbody>
</table>

For the matrices Wq, WK3, WK4, WK5 and W20, the robust version of these tests (R-LMERR and R-LMERR) renders the same results and LMLAG>LMERR, so the spatial lag model is appropriate. However, when these tests are computed with W30 and W40, the spatial error model becomes more appropriate. Notwithstanding that, our research is based on local data and, from an economic perspective, any attempt at considering long distance is difficult to justify. In fact, when these matrices are used, we lose the advantage of working with a high level of spatial de-aggregation. Consequently, a spatial lag specification has been chosen and, more specifically, one based on both the economic theoretical framework\(^{14}\) and the results of the specification test. Similarly, LeSage and Pace (2009) assert that spatial lag models have been used in contexts where there is a theoretical motivation for \( Y \) to be dependent on neighboring values of \( Y \).

\(^{14}\)These results bring up one of the unsolved questions in spatial econometrics: the selection of the spatial weight matrix (Fernández-Vázquez et al. 2009).
Molho (1995) and Patacchini and Zenou (2007) provide theoretical explanation for 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 ($|I - \rho W|$ in the SAR model and $|I - \theta W|$ in the SEM model) represent the main problem of this method. This 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 have pointed out the inefficiency of 2SLS estimators (2SLSE), especially when compared to the maximum-likelihood estimator (MLE). Furthermore, 2SLSE will be inconsistent when 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. More recently, Lin and Lee (2010) have shown the robustness of the GMM estimators under unknown heteroskedasticity—a context in which the MLE is usually inconsistent.

The local unemployment rate equation has been estimated by means of ML, 2SLS and GMM methods. The results are shown in Table 6. We have also considered some spatial weight matrices based on either geographic contiguity (municipalities sharing boundaries) or distance between municipalities, but we present only the results obtained with a k-nearest neighbor matrix $k=5$.

Generally speaking, it should be noted that the results are qualitatively similar across the different methods. Also, they are quantitatively the same when 2SLS and GMM are compared. The first column in Table 6 shows the estimation results of the 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. Additionally, a spatial Hausman test has been applied to detect the presence of omitted variables. The null hypothesis$^{15}$ (statistic value=522.52***) may be rejected in this case and hence a model with a spatial lag of the dependent variable is more plausible than a spatial error model.

According to the results obtained, the unemployment rates in the Spanish municipalities show 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

---

$^{15}$ The Hausman test statistic follows a chi-squared distribution with degrees of freedom equal to the number of explanatory variables.
of neighboring 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. A possible explanation for this smaller value could lie in the non-normality of the error term and the aforementioned heteroskedasticity problem. Therefore, 2SLS and GMM are more adequate.

Table 6. Estimation results (local unemployment rate) for spatial models

<table>
<thead>
<tr>
<th>Parameter</th>
<th>ML</th>
<th>2SLS</th>
<th>GMM</th>
<th>GMM-HETEROS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-1.4273</td>
<td>-0.7866</td>
<td>-0.6266</td>
<td>-0.4339</td>
</tr>
<tr>
<td>$A_1^{1a}$ with $\lambda = -0.10$</td>
<td>-0.0279</td>
<td>-0.0142</td>
<td>-0.009</td>
<td>-0.006</td>
</tr>
<tr>
<td>FLF</td>
<td>0.5395</td>
<td>0.3441</td>
<td>0.2744</td>
<td>0.223</td>
</tr>
<tr>
<td>MLF</td>
<td>-0.1243</td>
<td>-0.0279</td>
<td>-0.0142</td>
<td>-0.009</td>
</tr>
<tr>
<td>HH</td>
<td>0.1867</td>
<td>0.10548</td>
<td>0.0904</td>
<td>0.0729</td>
</tr>
<tr>
<td>LL</td>
<td>-0.1243</td>
<td>-0.0279</td>
<td>-0.0142</td>
<td>-0.009</td>
</tr>
<tr>
<td>HLLI</td>
<td>2.5954</td>
<td>1.4919</td>
<td>1.2505</td>
<td>0.6756</td>
</tr>
<tr>
<td>PRI</td>
<td>-0.1243</td>
<td>-0.0279</td>
<td>-0.0142</td>
<td>-0.009</td>
</tr>
<tr>
<td>SEC</td>
<td>0.1867</td>
<td>0.10548</td>
<td>0.0904</td>
<td>0.0729</td>
</tr>
<tr>
<td>UNI</td>
<td>-1.3766</td>
<td>-1.0521</td>
<td>-0.9873</td>
<td>-0.6419</td>
</tr>
<tr>
<td>FOR</td>
<td>-0.1243</td>
<td>-0.0279</td>
<td>-0.0142</td>
<td>-0.009</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.5451</td>
<td>0.7856</td>
<td>0.8318</td>
<td>0.8712</td>
</tr>
<tr>
<td>LRho</td>
<td>1666.3</td>
<td>-0.6677</td>
<td>-0.6677</td>
<td>-0.6677</td>
</tr>
<tr>
<td>Lambda</td>
<td></td>
<td></td>
<td>-0.6677</td>
<td>-0.6677</td>
</tr>
<tr>
<td>Wald</td>
<td></td>
<td></td>
<td>50.726</td>
<td>50.726</td>
</tr>
<tr>
<td>Heteroskedasticity (Breusch-Pagan)</td>
<td>431.7991</td>
<td>376.9682</td>
<td>428.5944</td>
<td>446.1599</td>
</tr>
<tr>
<td>Kolmogorov-Smirnov</td>
<td>0.2418</td>
<td>0.2375</td>
<td>0.2061</td>
<td>0.2302</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.4228</td>
<td>0.4636</td>
<td>0.4607</td>
<td>0.4550</td>
</tr>
<tr>
<td>LM test for residual autocorrelation</td>
<td>612.79</td>
<td></td>
<td>612.79</td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>7,754</td>
<td>7,754</td>
<td>7,754</td>
<td>7,754</td>
</tr>
<tr>
<td>Sigma^2</td>
<td>0.1676</td>
<td>0.1630</td>
<td>0.1638</td>
<td>0.1658</td>
</tr>
</tbody>
</table>

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

In accordance with our hypotheses, local unemployment rates seem to be inversely related to the accessibility measure. Its coefficient is significant and negative, but it is constrained 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 accessibility elasticity is lower when spatial autocorrelation is included explicitly into the model. However, the interpretation of the parameters is more complicated in models containing the spatial lag of the dependent variable. In the spatial lag model, any change in the dependent variable for a single region may affect the dependent variable in all the other regions. Thus, a change in one explanatory variable in the municipality $i$ will not only exert a direct effect on its own unemployment rate, but also an indirect effect on the unemployment rate of neighboring municipalities.

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16 Lin and Lee (2010) show that the MLE estimator is generally inconsistent with unknown heteroskedasticity if the SAR model were estimated as if the disturbances were i.i.d.
rates of other municipalities. As consequence, the impact that a change in one of the explanatory variables has on the dependent variable of a region is not usually equal to its estimated coefficient.

Pace and Lesage (2006) propose new measures to collect all these interactions between regions so that we may reach a correct interpretation of the spatial models and distinguish between the direct and the indirect impact. The direct impact shows the average response of the dependent variable to independent variables, including feedback influences that arise from impacts passing through neighbors and back to the municipality itself\(^{17}\). The indirect impact tackles the effect that any change in a region has on others and how changes in all regions affect a region. Table 7 shows the estimated direct and indirect impacts by means of 2SLS and GMM.

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

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

Note: Z-statistics in parentheses are based on 2000 simulated draws of the parameters.

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

Even more interesting is the estimation result of the indirect impact, which is significant and five times higher than the coefficient estimate in the GMM model (3.5 times higher than that in the 2SLS model), showing a positive influence of the accessibility to placement offices across the spatial dependences between municipalities. The total impacts are -0.050 and -0.0662 for GMM and 2SLS respectively. This means that if accessibility increases by 1%, the unemployment rate decreases by 0.0504% / 0.0662%. All coefficients of the independent variables —except MLF, PRI and FOR— are statistically significant (Table 6). In addition to that, there is evidence in support of the geographical perspective hypothesis on persistent unemployment. The coefficient of the

\(^{17}\)The main diagonal of higher order spatial weight matrices is non-zero, which allows us to collect these feedback effects.
dummy variable HH is positive, which means that a municipality belonging to an HH cluster is strongly constrained by this spatial pattern. However, the variable LL is not significant in 2SLS and GMM models. It is significant and negative in the ML estimation, which means that a municipality belonging to a LL cluster receives a positive influence in terms of unemployment rates.

Regarding the estimation results of the educational attainment variables, the percentage of university graduates is significant and negative, whereas those of illiterates and secondary education graduates are significant and positive. As expected, the coefficient of secondary education graduates is lower than that of illiterates.

Finally, the residuals of the spatial lag model have been analyzed to check whether the spatial autocorrelation had been fully removed. The result of the LM test is significant to reject the null hypothesis of no spatial correlation in the residual errors. However, as we explained above, the heteroskedasticity problem points to the specification of a model in which such unknown heteroskedasticity in the error term may be controlled.

As we described above, the GMM estimation is a good choice when normality cannot be verified. Recently, Kelejian and Prucha (2007) and Arraiz et al. (2010) have extended the GMM approach to a spatial autoregressive disturbance process with heteroskedasticity innovations. It should also be noted that this specification allows for heteroskedasticity of unknown form. The fourth column in Table 6 shows the estimation results of the model by GMM with heteroskedasticity innovations. The estimated coefficient of the accessibility measure is negative and statistically significant. We have obtained a strong spatial dependence between local unemployment rates with a significant spatial effect.

Thus, the presence of heteroskedasticity has no impact on the coefficient estimates of this empirical model when 2SLS and GMM methods are compared. All these approaches have been applied to the study of local unemployment rates and we have found that the accessibility measure helps to reduce them.
5. Conclusions and policy recommendations

We have obtained that there are spatial differences across the local employment offices in Spain. We have computed the number of unemployed persons per employment office and found that, in some autonomous communities, the number of placement offices is far below the unemployed they have to attend to (especially Madrid, the Canary Islands, the Valencian Community and Catalonia). Even though employment offices are located around municipalities with high numbers of jobless, it may be concluded that, in terms of the accessibility to employment offices, this distribution is synonymous with spatial inequity.

In addition to that, we have improved the precision of the measure of the level of accessibility of a municipality to its corresponding employment office by including the size of the employment office catchment area in the accessibility measure. Also, we have detected the main clusters of municipalities with low accessibility to employment offices and those with high unemployment in 2009.

On one side, the results suggest that policy makers should strive to improve the accessibility to placement offices in the municipalities with low accessibility levels so that adequate assistance to find suitable employment may be ensured to every job-seeker. On the other side, we have brought out that accessibility has a significant effect on unemployment rates.

Using ML, 2SLS and GMM results, we have shown a strong spatial correlation between unemployment rates, i.e. neighborhood influences are very important in labor markets. This view is consistent with other empirical studies such as Molho (1995) and Patacchini and Zenou (2007) and, therefore, the spatial perspective cannot be ignored in the analysis of the Spanish labor market. Furthermore, in accordance with our hypotheses, unemployment rates appear to be inversely related to the accessibility measure. In addition to that, when we compute the direct and indirect impacts of the accessibility measure on unemployment rates, the indirect impact is shown to be higher than the coefficient estimate in 2SLS and GMM models. This, in turn, shows a positive influence on the reduction of unemployment rates across the spatial interactions between municipalities. Also, it does strengthen our conclusions about the impact of the accessibility measures on unemployment rates.

As consequence of the decentralization process over the last 20 years in Spain, the autonomous communities have taken over the active labor market policies and the creation and/or reorganization of the employment offices and their catchment areas. We recommend the creation of new employment offices so that the size of 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 efficiency of the several types of services provided at each employment office.
References


