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Working Paper Series

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ECINEQ WP 2005 – 08

ECINEQ 2005-08
November 2005

www.ecineq.org

# The geographical concentration of unemployment: A male-female comparison in Spain*

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**Abstract**

This paper aims at complementing the approach presented by Johnston et al. (2003) with tools from the literature on economic geography and income distribution in order to perform a thorough analysis of the spatial concentration of unemployment. Apart from using such empirical procedures in the field of labour economy, the paper shows the complementarities that both approaches have when trying to look into distributive issues from a spatial perspective. For that purpose, the paper analyses the spatial distribution of unemployment in Spain, with a thorough analysis of the differences between male and female patterns.

Keywords: unemployment; spatial concentration; municipalities.
JEL Classification:

* Financial support from the Spanish Ministry of Education and Science, via grants SEJ2005-07637-C02-01/ECON and SEJ2004-07373-C03-02/ECON, and from FEDER are gratefully acknowledged. We also want to thank Luis Toharia for his help with the data.

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## 1. Introduction

In the literature on economic geography there is a wide consensus regarding the relevance of studying agglomeration patterns of economic activities. In this respect, many theoretical and empirical papers have been written to look into this aspect of spatial analysis (Combes and Overman, 2004; Amiti, 1999; and Kim 1995, amongst others). The study of unemployment location offers a complementary viewpoint of the same phenomenon, as it allows for the detection of agglomeration patterns in the population outside the labour market. This issue, however, has not been widely studied in the literature, where efforts have been oriented towards evidencing and explaining the differences in unemployment rates among countries or regions rather than towards analysing spatial concentration. An exception to this trend is the paper by Overman and Puga (2002) which analyses unemployment clusters in Europe to determine the importance of the transnational and regional dimension in the creation of such clusters. Likewise, Johnston *et al.* (2003), from a different perspective, present a simple graphic procedure to analyse to what extent individuals in a particular group are located in areas where there are numerous similar individuals. These authors analyse the importance of the level of territorial disaggregation in their study of the geographical concentration of male unemployment in England and Wales. They suggest that this aspect should be taken into account in the design of area-based public employment policies.

This paper tries to complement that approach with other tools from the literature on economic geography and income distribution, which will be used to further analyse the spatial concentration of unemployment. Apart from borrowing these empirical procedures in the field of labour economics, this paper will show the complementarities that both approaches can offer when looking into distributive issues from a territorial perspective. These tools will allow us to analyse the spatial distribution of unemployment in Spain, focusing on the differences between male and female patterns. In this case, in comparison to other previous studies, the level of territorial disaggregation used will be the municipality rather than the province or region. This disaggregation level contributes to a more profitable analysis, since the spatial dimension is precisely the focus of this paper.[1]

[1] López-Bazo *et al.* (2002, 2005) analyse other spatial aspects of the distribution of unemployment in Spain and try to explain, through an econometric model, the evolution of differences in unemployment rates at provincial level. Toharia (2003; 2005), amongst others, analyses the evolution of unemployment in Spain in the last few decades, although he does not deeply analyse its spatial dimension beyond regional differences.

In keeping with our purposes, this paper uses the Maurel and Sédillot (1999) index, which was initially proposed to analyse the geographic concentration of industries in France.[2] This approach adds a new element to the spatial analysis proposed by Johnson *et al.* (2003): to find out whether the distribution of the unemployed has a close relationship to the distribution of the population as a whole.[3] For a deeper analysis of distributive aspects, this paper takes a look at the literature on income distribution (the Lorenz curve and the Gini and Theil indices).[4] In this way, population distribution is also considered, but by means of indices that verify axiomatic properties associated with different normative concepts of inequality discussed in the literature. Furthermore, we will use the decomposition of the Lorenz curve by subgroups, as recently proposed by Bishop *et al.* (2003), to determine the contribution of municipalities, classified according to their size, at different points of the distribution. On the other hand, the Theil and Gini indices, as they have the property of completeness**,** will help not just to quantify the level of inequality but also to draw comparisons in those cases in which the Lorenz criteria are not conclusive. Another advantage of the Theil indices is that they can be decomposed. This is something that will be explored in this study both to determine the contribution of municipality subgroups to the concentration of unemployment and to acknowledge the different contribution of men and women.

All this will enable us to reveal the different situation of men and women in large cities, as well as the differences that these cities show in comparison to smaller towns. These aspects should be taken into account in the design of public employment policies, especially if they aim at reducing inequalities between the sexes. Mention should be made to the fact that Spain is not only a country with a large female unemployment rate, but also one with very significant differences between the male and female rates. In fact, according to an OECD (2004) report, in Spain the male unemployment rate was 8.2% in 2003, while the female unemployment rate was 16%. If these data are compared with those of neighbouring

[2] This has been later applied to other countries. Thus, for example, Alonso-Villar *et al.* (2004) did use it for the Spanish case.
[3] Both total population and a particular subgroup could be considered as reference population. For example: the economically active population, people of working age, or the population collecting unemployment benefits.
[4] Some of these indices have not only been used to analyse income inequality, but also to examine inequality in the provision of health services (Quadrado *et al.*, 2001, amongst others) and in levels of industrial activity (Brülhart and Traeger, 2005). One of the indices of the Theil family has also been used by Garrido and Toharia (1996) to analyse the evolution of unemployment in Spain at regional level.

countries, the situation looks even worse. Thus, in 2003 the female unemployment rate in the European Union was 8.6% (almost half the Spanish figure), while the male unemployment rate was 7.2% (just one point less). However, despite these important differences, national rates do not enable us to find out the discrepancies between men and women at other levels of territorial disaggregation. This is a really relevant matter if one realises that unemployment in Spain also shows important internal disparities, both at regional and provincial levels.[5] Therefore, the analysis of spatial differences in unemployment between the sexes should have an increased weight, not only for its academic interest, but also and above all for its potential repercussion on the design of area-based public policies aimed at reducing existing inequalities between men and women in the labour market.

The paper is structured as follows. Section 2 gives a detailed explanation of the methodologies that will be used in Section 3 for an analysis of the spatial distribution of unemployed men and women. The main conclusions are introduced in Section 4.

## 2. Methodology

As already stated, this paper aims at analysing the spatial distribution of the unemployed in Spain, in order to identify potential differences between the male and female distribution. For this purpose, we will use methodologies developed both in the literature on economic geography and that on income distribution, and we will adapt them to our case study.

- ***Economic Geography***

First, we are going to use a procedure, proposed by Johnston *et al.* (2003), that allows us to show graphically the distribution of unemployment. This method is particularly interesting as it analyses the location of the unemployed against that of other unemployed. In fact, this concentration profile provides information about the percentage of unemployed (against the

[5] Thus, in 2003 the difference between the highest and lowest regional unemployment rates was 13 percentage points, with Andalucia (21%) and Aragon (around 8%) at the two extremes of the distribution (see Toharia, 2005).

total number of unemployed) living in locations with unemployment rates above any given threshold.[6]

If the unemployed were equally distributed among municipalities, even if they were not necessarily present in all of them, so that the unemployment rate in those locations was, for example, 15% (and zero in all remaining towns), the curve would have two separate plots. The first horizontal line would be at the high of 100% until the value of 15% on the x-axis, and the other horizontal line would remain at 0% until the end. If said percentage were 80% instead of 15%, the upper line would be longer and the lower one, shorter. Furthermore, if all the unemployed were spatially concentrated in a few municipalities without anybody else living in them, the curve would become a horizontal straight line at 100% until the end, as the percentage of the unemployed living in municipalities with unemployment rates above any $x \in [0,100]$ would be 100%. Thus, for a given number of unemployed, if they are evenly distributed in all locations the unemployment rate will be the same for all of them, and therefore the figure will have a small upper line and a large lower line. If the same unemployed are located only in some few places, the unemployment rates there will be far higher, and the figure will accordingly have a large upper line and a short lower line. In intermediate situations, this curve is usually smoother so that the percentage of the unemployed living in locations with unemployment rates above the threshold gradually decreases when the threshold increases. In other words, the percentage is high when unemployment rates are low, if they are high, the opposite effect occurs, but without gaps of 100%, as in previous examples. On the other hand, the further the curve turns to the right, the higher the spatial concentration of the unemployed will be.[7]

Second, we employ the spatial concentration index used in the literature on industrial location to determine whether the distribution of the unemployed among locations is closely related to the distribution of the population as a whole. For this purpose, we use the concentration index proposed by Maurel and Sédillot (1999) (M-S), which is as follows:

[6] This curve is somewhat similar to the unemployment distribution function, but instead of accumulating individuals living in municipalities with unemployment rates below the threshold, it accumulates the unemployed living in municipalities with rates above that threshold.

[7] Note that this curve is not affected by changes in the population size of municipalities with unemployment rates equal to zero. As they do not have any unemployed, they do not participate in the unemployment distribution. As we will see later, other indices, such as the Maurel and Sédillot (1999) index, are however sensitive to this issue.

$$\gamma = \frac{C - \frac{1}{N}}{1 - \frac{1}{N}} \quad ,$$

where

$$C = \frac{\sum_i s_i^{\,2} - \sum_i x_i^{\,2}}{1 - \sum_i x_i^{\,2}} = \frac{\sum_i (s_i - x_i)(s_i + x_i)}{1 - \sum_i x_i^{\,2}} \quad ,$$

$s_i = \frac{n_i}{N}$ being the proportion of the unemployed in municipality *i*, that is, the quotient between the number of unemployed in location *i* ($n_i$), and the total number of unemployed ($N = \sum_i n_i$); and $x_i = \frac{p_i}{P}$ being the proportion of population settled in that location, i.e., the quotient between the population in location *i* ($p_i$) and total population ($P = \sum_i p_i$).[8] In our empirical analysis the reference population will be the people in the working age group.

This index can be derived from a localisation model in which the unemployed (in the reference paper this was used instead for the companies in a particular sector) would be located in one location or another depending on its characteristics.[9] If the unemployed (the companies in the sector, respectively) were randomly distributed all over the territory, one could expect that in those places where the population (the economic activity, respectively) were double in number, the number of the unemployed (the firms in the sector, respectively) would also be double and the index would be equal to 0. On the contrary, if the distribution were not random, discrepancies would be found between the distribution of the unemployed and that of the reference population. This index estimates precisely those discrepancies in such a way that, the more the unemployed are present in a larger population, the more important these discrepancies become. In fact, the *C*'s numerator can be written as follows:

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[8] In our case index, $\gamma$ is very similar to index C, as the number of unemployed, *N*, is very high. See the properties of this index in Maurel and Sédillot (1999) when considering the number of companies and not their size.

[9] In Maurel and Sédillot (1999), the location of a firm could depend on the natural characteristics of the area, or on the possible externalities due to proximity between plants. In our case we can interpret the probability of an unemployed person to be in a particular place depending on the characteristics of that area, such as its productive structure, the number of companies, turnover, etc.

$\sum_i (s_i - x_i)(s_i + x_i)$ and thus, if in a municipality the proportion of the unemployed ($s_i$) is larger than its population proportion ($x_i$), the difference will be positive. *Ceteris paribus*, the higher the population in that location, the stronger influence it will have on the index. In other words, the γ index has a high positive value if in large cities the proportion of the unemployed is higher than its population weight. If small municipalities have a proportion of the unemployed higher than their demographic weight, their contribution will also be positive, although it is generally smaller in number, unless the proportion of the unemployed in such a municipality is extraordinarily large.[10]

In theory, this index can take values between –1 and 1, although empirical evidence for industrial localization shows that the range of values is far more reduced. In any case, this index does not yield a value that can be interpreted in isolation, but always in comparison to others. Thus, this paper calculates its value for different population subgroups (by municipality size and sex), which will enable us to assess existing differences.

- ***Income distribution***

Third, we will look back at the literature on income distribution, namely the Lorenz curve and the Gini and Theil indices, in order to measure the degree of spatial concentration of the unemployed. In this way, we can also take the distribution of the population itself into account, but taking indices that verify various axiomatic properties assigned to various normative concepts of inequality already discussed in the literature. In any case, these indicators have not only been used to measure the differences in income levels between

[10] On account of all these factors, let us note that the M-S index is highly sensitive to the size of municipalities considered in the analysis. In fact, if in a particular distribution of municipalities each were disaggregated in $m_i$ smaller and equal municipalities, where the number of unemployed were evenly distributed among all of them, the M-S index would reduce its value in absolute value, as:

$$\left|\frac{(s_i - x_i)(s_i + x_i)}{1-\sum (x_i)^2}\right| = \left|\frac{m_i^2\left(\frac{s_i}{m_i}-\frac{x_i}{m_i}\right)\left(\frac{s_i}{m_i}+\frac{x_i}{m_i}\right)}{1-\sum m_i^2\left(\frac{x_i}{m_i}\right)^2}\right| > \left|\frac{m_i\left(\frac{s_i}{m_i}-\frac{x_i}{m_i}\right)\left(\frac{s_i}{m_i}+\frac{x_i}{m_i}\right)}{1-\sum m_i\left(\frac{x_i}{m_i}\right)^2}\right|.$$

This does not occur, however, with inequality indices.

individuals in a particular economy, but also to quantify the geographical concentration level of economic activities.[11]

In order to construct our Lorenz curve of unemployment, first let the different municipalities line up in ascending order of the ratio $\left(\frac{s_i}{x_i}\right)$, where the numerator is the proportion of the unemployed *i* against the total number of unemployed, and the denominator is the proportion of the population in the given location. This quotient equals the unemployment rate at *i*, divided by the unemployment rate of that economy, so that ranking by the above-mentioned ratio is equivalent to doing it by municipal unemployment rates. Next, the cumulative proportion of the population is shown on the horizontal axis and the cumulative proportion of unemployed, against the total unemployed, is shown on the vertical axis. Accumulating the unemployed at municipal level is the same as accumulating unemployment rates artificially assigned to a representative individual in each municipality, weighted by the population living in each of them.[12] Thus, the number of the unemployed in each municipality would play the role of the "income" variable of that municipality in a hypothetical analysis of income distribution, while the unemployment rate in the municipality *i* would be like the individual "income" of each of its inhabitants. In our case, of course, all individuals in a given municipality face the same unemployment rate, i.e., they would earn the same "income", which would be equal to the average "income" of their municipality.[13]

This leads to a double interpretation of the Lorenz curve, as we can think in terms of cumulative proportions of the unemployed, or of cumulative proportions of unemployment rates (weighted by population size). Therefore, when the Lorenz curve is far from the diagonal, we can say that the unemployed population is spatially concentrated, or else we can say that there is inequality in the municipal unemployment rates.[14] If the Lorenz curve for a particular distribution were higher in every point than that of another alternative distribution,

[11] Krugman (1991) was the first to translate these ideas into the field of industrial location, but he did not use a Lorenz curve, in which accumulation is undertaken in ascending order, but a symmetrical curve obtained through an accumulation in descending order. Also see Amiti (1999) and Kim (1995).

[12] Note that the number of unemployed in a particular location is the unemployment rate multiplied by its population.

[13] This situation also happens in income distribution analyses when we have grouped data, as, for example, per household. In this way, the income assigned to each of the members of a household is the per capita income, or in general, the equivalent income obtained using some equivalence scale.

[14] Let us note that the 45 degree line represents the situation of maximum equity in unemployment distribution, where all municipalities have exactly the same unemployment rate and, therefore, the geographical distribution of unemployment coincides with that of the reference population (the working age group).

the robustness of the Lorenz criterion would make us claim not only that the first distribution shows smaller levels of inequality/concentration according to Lorenz, but also according to any complete inequality index consistent with it. One of those indices is the Gini coefficient, which measures the “distance” from the Lorenz curve to the 45 degree line. More precisely, the expression can be written in our case as follows:

$$G = \frac{\sum_{i,j} x_i \cdot x_j \cdot \left| \overline{u}_i - \overline{u}_j \right|}{2\overline{U}} ,$$

where $\overline{u}_i = \frac{n_i}{p_i}$ is the unemployment rate of municipality *i*, and $\overline{U} = \frac{N}{P}$ the unemployment rate in the economy as a whole.

The Lorenz curve can be decomposed using different population subgroups (in our case, municipal subgroups designed according to their size), so that in each cumulative percentile we can see the contribution of those subgroups to the Lorenz ordinate. More precisely, according to Bishop *et al*. (2003), we can write

$$L(\tau,u) = \sum_{k=1}^{K} s^{(k)} \cdot L(\tau,u^{(k)}) ,$$

where $L(\tau,u)$ represents the Lorenz curve of the *u* distribution in the percentile $\tau$ (i.e., the proportion of unemployed accumulated until that percentile), $s^{(k)}$ represents the proportion of the unemployed in the *k* subgroup (against the total unemployed), *K* is the total number of subgroups in which the population has been divided and $L(\tau,u^{(k)})$ is the *k* subgroup’s cumulative proportion of the unemployed until percentile $\tau$ of the total distribution (*u*). Let us note that functions $L(\tau,u^{(k)})$ are not strictly the Lorenz curves of each subgroup, since they do not represent the cumulative percentage of the unemployed in a given subgroup until reaching its own percentile, $\tau^{(k)}$, but until the total population percentile, $\tau$. This decomposition is of great interest, as it will allow us to improve our analysis in two ways. On the one hand, the expression

$$LC_k = \frac{s^{(k)} L(\tau,u^{(k)})}{L(\tau,u)}$$

provides information about the contribution of each subgroup to the Lorenz ordinate in the corresponding percentile. On the other hand, function $L(\tau,u^{(k)})$ will enable us to determine how the unemployed of subgroup $k$ are distributed among the percentiles of the whole distribution.

The Theil indices are other inequality indicators we will refer to in the empirical analysis. Although these indices do not offer such an intuitive interpretation of the Lorenz curve such as the Gini coefficient, they are equally consistent with this criterion[15] and they do verify properties that make them particularly interesting for the study of inequality. These indices constitute a family as their normative properties are gradually different depending on the value of the inequality aversion parameter that we choose, and thus they allow us to compare results and draw conclusions on their potential discrepancies in concrete empirical situations. The expressions of Theil indices used and adapted in our study of unemployment are the following:

$$T_{-1} = \frac{1}{2}\sum_i x_i\left[\left(\frac{\bar{u}_i}{\bar{\bar{U}}}\right)^{-1} - 1\right],$$

$$T_0 = \sum_i x_i \ln\left(\frac{\bar{\bar{U}}}{\bar{u}_i}\right),$$

$$T_1 = \sum_i x_i\left(\frac{\bar{u}_i}{\bar{\bar{U}}}\right)\ln\left(\frac{\bar{u}_i}{\bar{\bar{U}}}\right),$$

$$T_2 = \frac{1}{2}\sum_i x_i\left[\left(\frac{\bar{u}_i}{\bar{\bar{U}}}\right)^{2} - 1\right].$$

These indices allow us to improve the distributive analysis obtained by means of the Lorenz curve. First, as they are complete indices, they permit us to quantify the level of inequality and draw a comparison in those cases where the Lorenz criterion is not conclusive, as there are intersections between curves.[16] Second, another advantage of this family of indices is that its members can be decomposed. This is an interesting property for empirical work, wherein it becomes relevant to know the population subgroup in which inequality is concentrated, as well as the factors contributing to its best explanation. In this regard, the literature on inequality has focused on characterising two types of decomposition:

[15] In other words, if a particular Lorenz curve reflects more inequality than another one, the Theil indices will have a higher value in the first case than in the second.
[16] The same thing occurs with the Gini coefficient. Potential discrepancies in the final results obtained with different indices will thus reflect the different notions of inequality behind normative properties that each index aims to verify. Only when there are no intersections between the Lorenz curves will all these coefficients yield consistent results with one another.

i) **Inequality decomposition by subpopulations.** Sometimes it is useful to divide the target population in different subgroups according to particular relevant characteristics to measure the contribution of each to total inequality. In our case, the population will be partitioned by municipality size. A decomposable index can be expressed as a function of inequality within every one of these subgroups (*within*) and inequality between those groups (*between*).[17] The most widely used concept of subgroup decomposition is that of additive separability proposed by Shorrocks (1980). The Theil indices with an inequality aversion parameter equal to 0 and 1 verify this property from a decomposition that allows for intuitive interpretation of the weighting factors of the *within* components. By using these indices we will not only calculate what kind of municipalities have a higher level of responsibility in the level of unemployment inequality/concentration, but also see if the size variable is an important dimension in the phenomenon of unemployment concentration. Decompositions derived from each of these indices can be expressed as follows for our case:

$$T_0 = \sum_k x^{(k)} T_0^{(k)} + \sum_i x_i \ln\left(\frac{\overline{U}}{\overline{u}^{(k)}}\right),$$

$$T_1 = \sum_k s^{(k)} T_1^{(k)} + \sum_i x_i \frac{\overline{u}^{(k)}}{\overline{U}} \ln\left(\frac{\overline{u}^{(k)}}{\overline{U}}\right),$$

where $x^{(k)}$ is the population weight represented by subgroup $k$, $T^{(k)}$ the value of the Theil index for that subgroup, and $\overline{u}^{(k)}$ its unemployment rate. The first addend of the above formulae represents the *within* component, i.e., the weighted sum of inequalities inside each population subgroup, while the second addend reflects the *between* component, where the index is applied to an artificial distribution in which each municipality is assigned the average unemployment rate of its subgroup, and thus internal inequalities are eliminated.

ii) **Inequality decomposition by factor components.** In the literature on income distribution, an index is said to verify this property if it can determine what share of total inequality can be attributed to inequality in each of the different types of income according to its nature (capital, labour, social benefits, etc) or earner.[18] In the field of unemployment, apart from analysing the contribution of different types of municipalities, as mentioned above, it can also be useful to analyse the distribution of unemployment in terms of the characteristics of the unemployed,

[17] This is generally so with some trivial exceptions because total inequality will always be higher than the sum of existing inequalities of the different parts, as heterogeneity of subgroups is an additional source of diversity in itself.

[18] See Shorrocks (1982 and 1988) for a discussion of the different ways to quantify the contribution of each income source to total inequality.

such as sex, race, age, occupational sector, time unemployed, etc. In this study we want to analyse the sex variable in order to assess the differences in male and female unemployment concentration. Therefore, we have decomposed the total unemployed population in each municipality into unemployed men and women. This decomposition enables us to consider three different unemployment distributions: the total distribution and that of each of the two groups. Let $u_c$ be the distribution resulting from dividing the number of unemployed in the group *c* (men or women) taken separately in each municipality by the total population of that area. Let variable *u* be the distribution of municipal unemployment rates (the number of unemployed individuals in each municipality divided by its population size). The proportion in which the component/factor *c* contributes to total inequality, according to Shorrocks (1980), can be expressed here as related to the $T_2$ index as follows:[19]

$$S_c = \rho_c \left( \frac{\overline{u}_c}{\overline{U}} \right) \sqrt{\frac{T_{2c}}{T_2}} \ ,$$

where the subindex *c* represents the male (*m*) or female (*f*) component of unemployment and $\rho_c$ is the correlation coefficient between the distribution *u* and the distribution $u_c$. $T_{2c}$ is the Theil index of parameter 2 applied to distribution $u_c$, and $\overline{u}_c$ is the mean (weighted by municipality size) of such distribution. This mean coincides with the quotient between the number of unemployed in the group of men or women in all municipalities divided by total population. That is, it represents the male/female component of the aggregated unemployment rate, as: $\overline{U} = \overline{u}_m + \overline{u}_f$ .

## 3. Comparisons between male and female unemployment

### 3.1. Data sources

In order to carry out this study we need to know the unemployment rates at municipal level, as we are interested in working with the highest level possible of territorial disaggregation. The *Instituto Nacional de Estadística* (*INE*) has been conducting the *Encuesta de Población Activa* (*EPA*) for some decades now, following EUROSTAT's guidelines. This survey offers labour market information of a representative sample of Spanish households and it tends to be

[19] In Brülhart and Traeger (2005) this decomposition is used to analyse the concentration of economic activity in Europe per sector.

used for international comparisons. The *EPA* also yields the Spanish provincial and regional unemployment rates, but does not gather any municipal information. Therefore, we have to use an alternative unemployment database which comes from an administrative source: the job-seeker rolls supplied by the public employment services, *Servicio Público de Empleo Estatal* (*SPEE*). In particular, the *SPEE* has information about "unemployed employment seekers" (*DENOs*), which is a wider concept than the one traditionally used for registered unemployment, since it includes other groups that should be considered as unemployed if the international criteria adopted by the *EPA* were applied (Toharia, 2005). This new definition of unemployment has been used since 1998 in order to implement national employment action plans and is the result of the little credibility that EU authorities gave to the concept of registered unemployment as reference data to quantify the specific objectives of the plans. For this study, we have thus used the *DENOs* data of the Spanish municipalities for January 2005. These data are obtained through the new information systems of public employment services, which have been recently set up to improve the management of active employment policies (Toharia and Malo, 2005).

As we do not have access to data about the economically active at municipal level, the unemployment rate has been calculated by dividing the number of the unemployed according to the DENOs concept by the working age population (which in Spain is the group from 16 to 64 years of age).[20] In order to obtain the denominator, we have worked with data from the Census (*Padrón Continuo*) of the *INE* for 2004, as the municipal data for 2005 are not available yet.[21]

## 3.2. Results

### 3.2.1. The territorial dimension of unemployment

Density functions of municipal unemployment rates reflect significant differences between female and male unemployment. As we can see in Figure 1, the male distribution is further to

[20] Even if we had had access to municipal data on the economically active from the EPA, there is wide criticism about the use of such data as reference population when they are used together with data from an administrative source (Toharia, 2005).
[21] As we do not have an official figure for the economically active population per municipality, our unemployment rates do not take into account the effect generated by the lower participation rate of women. In any case, note that incorporating this issue would enable us to detect even more differences between the male and female unemployment rates.

the left and has a more skewed shape, which indicates that for men there is less dispersion and a lower average unemployment rate than for women. In fact, the average of female unemployment rates weighted by municipality size is 10.6%, and the simple average is 9%. However, for men the average is 6.7% in the first case and 5.7% in the second.[22] This seems to indicate that there is a large proportion of small municipalities with unemployment rates much lower than the average for both men and women. As regards the standard deviation, it is 5.1 for women and 2.9 for men (7.8 and 5, respectively, in the unweighted distributions)

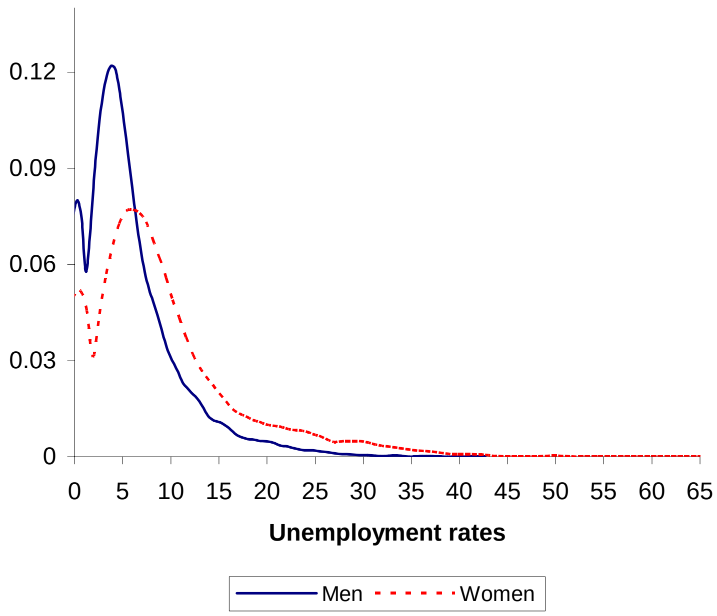


**Figure 1. Density functions of unemployment rates**

Let us now look at the distribution of the unemployed population among municipalities, because beyond determining their unemployment rates, we also aim to measure their proportion of the total unemployed population. For this purpose we now build the concentration profile curve, which yields information on the proportion of the unemployed living in the municipalities with unemployment rates above any given threshold. In order to obtain this curve, first the intervals of unemployment rates have to be defined and second the proportion of the unemployed, against the total unemployed, living in municipalities included in each interval has to be calculated (see Table 1). Thus, for example, the first column indicates that almost 3% of the unemployed women live in municipalities where the female unemployment rate is between 4% and 6%, while 19% of them live in municipalities with

[22] The average of municipal unemployment rates weighted by municipality size is precisely the national unemployment rate (number of unemployed divided by the working age population).

rates between 6% and 8%. Second, we gather the unemployed population above each threshold. In this way, as shown in the third column, over 77% of the unemployed women live in municipalities with rates above 8%, and almost 48% live in municipalities with rates over 12%. This means that almost half of the female unemployed live in municipalities whose female unemployment rates are a point above their average. On the other hand, we also note that fewer than 4% of the female unemployed are in municipalities with rates below (or equal to) 6%. The information on the table can be used to construct the concentration profile curve, with the unemployment rate thresholds on the horizontal axis and the proportion of the unemployed living in municipalities with unemployment rates above that threshold on the vertical axis.

| **Unemployment rates** | **Percentage of unemployed** | | **Cumulative percentage** | |
|---|---|---|---|---|
| | **Women** | **Men** | **Women** | **Men** |
| 0 | 0.00 | 0.00 | 100.00 | 100.00 |
| (0, **2**] | 0.02 | 0.21 | 99.98 | 99.79 |
| (2, **4**] | 0.34 | 5.24 | 99.63 | 94.55 |
| (4, **6**] | 2.98 | 30.90 | 96.65 | 63.65 |
| (6, **8**] | 19.13 | 22.45 | 77.51 | 41.19 |
| (8, **10**] | 18.66 | 19.95 | 58.86 | 21.24 |
| (10, **12**] | 11.07 | 11.23 | 47.79 | 10.02 |
| (12, **14**] | 15.15 | 4.29 | 32.63 | 5.73 |
| (14, **16**] | 9.74 | 1.84 | 22.90 | 3.89 |
| (16, **18**] | 7.01 | 1.24 | 15.88 | 2.65 |
| (18, **20**] | 3.37 | 0.89 | 12.52 | 1.76 |
| (20, **22**] | 2.43 | 0.62 | 10.09 | 1.14 |
| (22, **24**] | 2.19 | 0.43 | 7.89 | 0.71 |
| (24, **26**] | 1.36 | 0.33 | 6.53 | 0.38 |
| (26, **28**] | 1.43 | 0.22 | 5.10 | 0.16 |
| (28, **30**] | 1.73 | 0.05 | 3.37 | 0.11 |
| (30, **32**] | 0.99 | 0.04 | 2.38 | 0.07 |
| (32, **34**] | 0.66 | 0.03 | 1.72 | 0.04 |
| (34, **36**] | 0.58 | 0.00 | 1.14 | 0.04 |
| (36, **38**] | 0.66 | 0.04 | 0.49 | 0.01 |
| (38, **40**] | 0.49 | 0.01 | 0.00 | 0.00 |

**Table 1. Concentration profile values**

If we compare the functions of concentration profiles for men and women, as we can see in Figure 2, many differences become evident. Thus, while around 23% of the female unemployed are in municipalities with unemployment rates over 16% (almost six points above the female national average), only 10% of their male counterparts are in a similar situation (which corresponds to a threshold of 12%, i.e., six points over the male national average). Furthermore, 10% of the female unemployed live in municipalities with unemployment rates above 22% (a figure actually doubling their national average) while there are hardly any men above that threshold. This seems to indicate that the female unemployed are more concentrated in space than men, i.e., many of them live in municipalities with extremely high female unemployment rates. In fact, as we have just seen, half of the unemployed women are in municipalities with female unemployment rates over 12%, while almost half of the unemployed men live in municipalities with male unemployment rates below 7%, and furthermore, only 10% of them live in municipalities with rates over 12%.

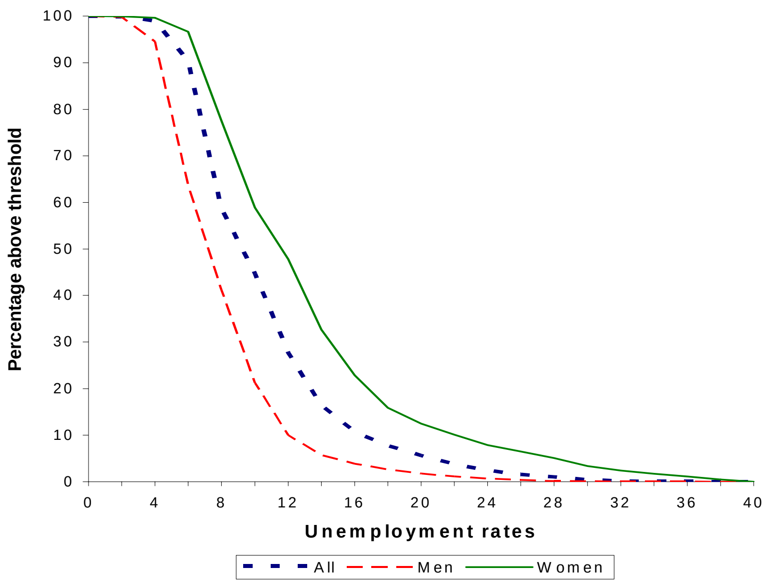


**Figure 2. Concentration profile curves**

One could reasonably expect that the distribution of the unemployed should be strongly conditioned by the distribution of the working age population. This issue, however, is just partially considered by the concentration profile curve, since only the population living in those municipalities with strictly positive unemployment rates are considered. In order to have a more comprehensive approach to this issue, we can use the M-S index. This index measures the discrepancies between the demographic weight and the proportion of the unemployed through a function of the weighted sum of the differences within each location. When we take this into consideration, significant differences are seen once again in the municipal distribution of male and female unemployment. Thus, even if the M-S index is below zero in both cases, for the female unemployed the value doubles the absolute value for males (see Table 2, last row). As already stated, this index becomes negative if there are many municipalities with a proportion of unemployed below their demographic weight, and especially if this happens in larger municipalities. Therefore, the result suggests that this situation is more prevalent for female unemployment than for male unemployment. Thus, we could conclude that female unemployment is relatively less localised in larger municipalities than male unemployment.

In order to go deeper into this analysis, we have partitioned municipalities into 5 categories: those of fewer than 2,000 inhabitants with an age range of 16 to 64 (subgroup 1), those having between 2,000 and 10,000 inhabitants (subgroup 2), those from 10,000 to 50,000 (subgroup 3), those from 50,000 to 100,000 (subgroup 4) and those with 100,000 or more working age individuals (subgroup 5). We can see that the M-S index for subgroup 5 is negative both for women and men, although it is higher in absolute value for the former. Thus, we can conclude that in large cities unemployment is not particularly intense, although the situation is more favourable for women than for men. On the contrary, the M-S value in the remaining subgroups has positive values, and once again they are higher for women than for men. This seems to indicate that unemployment is far more concentrated in small and mid-sized population centres than in large cities, especially for women.[23]

| | Women | Men |
|---|---|---|
| **Subgroup 1** | 0.00024 | 0.00022 |
| **Subgroup 2** | 0.00028 | 0.00023 |
| **Subgroup 3** | 0.00043 | 0.00039 |
| **Subgroup 4** | 0.00388 | 0.00303 |
| **Subgroup 5** | -0.01790 | -0.01141 |
| **All** | -0.00381 | -0.00153 |

**Table 2. Index of spatial concentration (Maurel and Sédillot, 1999)**

### 3.2.2. The distributive dimension of unemployment

As already stated, another way of taking the distribution of the working age population into account when quantifying the degree of spatial concentration of the unemployed is by using

[23] The fact that the M-S index has increasingly higher values in absolute value as the size of municipalities increases is not surprising, as we should note that it is very sensitive to the demographic weight of the units under study.

the Lorenz curve. The horizontal axis represents the cumulative proportions of the working age population and the vertical axis the cumulative proportions of the unemployed, once the municipalities have been ranked in ascending order by the ratio $\frac{s_i}{x_i}$, where the numerator is the proportion of the unemployed living in municipality *i*, against the total number of unemployed, and the denominator is its population proportion.

Figure 3 shows that the Lorenz curve for unemployed women is clearly below that of men after the third decile, while in the first deciles the opposite holds (although with almost insignificant differences between them). [24]

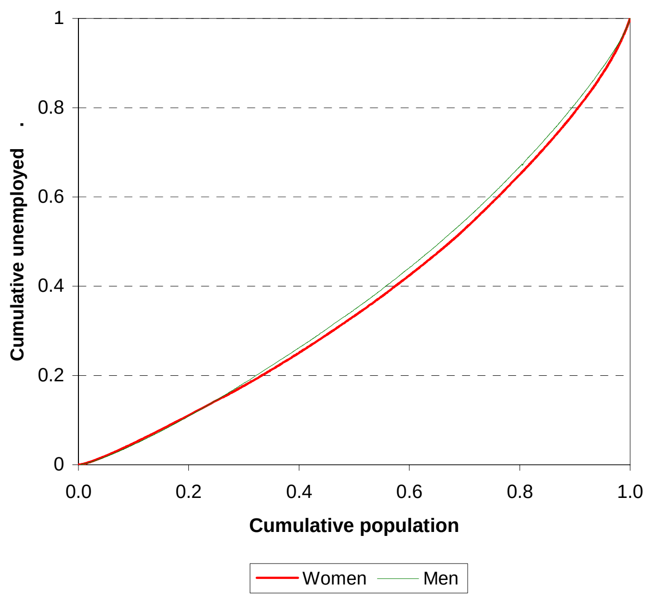


**Figure 3. Unemployment Lorenz curves**

The intersection between both curves does not allow us to determine what distribution shows a higher concentration level, as the Lorenz dominance criterion is not conclusive. To answer this question it is necessary to calculate complete inequality indices, even though it entails that more value judgments have to be included in the analysis. When calculating the Gini coefficient, we see that its value is higher for women than for men (0.24 against 0.22). Furthermore, as shown in Table 3A, for the four Theil indices considered, the levels reached

[24] Since we do not work with a sample but with the whole population of unemployed, statistical inference cannot be applied.

in the case of female unemployment are also higher than those attained in the male case.[25] Thus, we can state that unemployed women are more concentrated than men, even if we take their respective population distribution into consideration.

When using the factorial decomposition that allows the Theil 2 index to quantify the contribution of female and male unemployment to total inequality, we see that women contribute to a larger extent than men to the total concentration of the unemployed population, as could be expected. What is really remarkable is the magnitude of such a difference, as the contribution of women (64.1%) almost doubles that of men (35.9%), and is even higher than the value they should have according to their relative weight in the total unemployed population, of whom 60.7% are women.

| | **Unemployed (%)** | **Theil -1** | **Theil 0** | **Theil 1** | **Theil 2** | **Theil 2 decomposition by sex (%)** | **Theil 0 decomposition W – B (%)** | **Theil 1 decomposition W – B (%)** |
|---|---|---|---|---|---|---|---|---|
| **Men** | 39.28 | 0.0913 | 0.0815 | 0.0823 | 0.0928 | 35.87 | 99.72 - 0.28 | 99.72 - 0.28 |
| **Women** | 60.72 | 0.1006 | 0.0939 | 0.0990 | 0.1161 | 64.13 | 95.64 - 4.36 | 95.91 - 4.09 |

**Table 3A. Inequality indices**

In order to analyse the role of different types of municipalities in explaining the differences observed between men and women, we can use the decomposition of Theil 0 and Theil 1 indices by population subgroups. In Table 3B, the smaller municipalities (subgroups 1 and 2) show much higher internal inequality levels of unemployment than mid-sized and large municipalities, both for women and for men. This means that the percentage contribution of such municipalities to the *within* component (5th and 7th columns in Table 3B) is far higher than their population weight (2nd column). However, while for women the classification by municipality size enables us to explain about 4% of the total inequality, in the case of men, their contribution is practically non existent (as one can see in the *within-between* decomposition of the last two columns in Table 3A). This is due to the fact that the average male unemployment rates do not show any remarkable differences among the different groups of municipalities, while for large cities the female unemployment rate is clearly below the level reached in the remaining municipalities, which reinforces the results obtained by the M-

[25] As already mentioned, the members of the Theil index family are different to one another due to their higher or lower aversion to inequality. The chosen parameter values--those most widely used for empirical research--are the following: -1, 0, 1 and 2. In order to calculate these indices, those municipalities with an unemployment rate equal to zero had to be discarded, as some of those indicators are not defined for such a value. These municipalities have not been considered in the calculation of unemployment rates in these tables either.

S index. All this leads us to conclude that women living in larger municipalities seem to enjoy a better position in terms of employment. This, however, does not contradict the fact that in large municipalities the internal inequality level of female unemployment rates is remarkably higher than that of men (see Table 3B).[26]

| | **Unemployment rate** | **Population (%)** | **Unemployed (%)** | **Theil 0** | **Theil 0 *within* (%)** | **Theil 1** | **Theil 1 *within* (%)** |
|---|---|---|---|---|---|---|---|
| **MEN** | | | | | | | |
| **Subgroup 1** | 6.77 | 9.39 | 9.50 | 0.2462 | 28.46 | 0.2408 | 27.86 |
| **Subgroup 2** | 6.72 | 18.14 | 18.21 | 0.1284 | 28.67 | 0.1317 | 29.21 |
| **Subgroup 3** | 6.63 | 27.26 | 26.99 | 0.0633 | 21.25 | 0.0644 | 21.18 |
| **Subgroup 4** | 7.12 | 9.08 | 9.66 | 0.0524 | 5.86 | 0.0504 | 5.93 |
| **Subgroup 5** | 6.61 | 36.13 | 35.65 | 0.0354 | 15.76 | 0.0364 | 15.81 |
| **All** | 6.70 | 100 | 100 | 0.0815 | 100 | 0.0823 | 100 |
| **WOMEN** | | | | | | | |
| **Subgroup 1** | 11.08 | 8.37 | 8.77 | 0.2330 | 21.71 | 0.2259 | 20.86 |
| **Subgroup 2** | 11.80 | 17.40 | 19.41 | 0.1380 | 26.73 | 0.1435 | 29.35 |
| **Subgroup 3** | 11.06 | 26.95 | 28.17 | 0.0825 | 24.76 | 0.0867 | 25.73 |
| **Subgroup 4** | 11.21 | 9.37 | 9.93 | 0.0760 | 7.93 | 0.0724 | 7.58 |
| **Subgroup 5** | 9.41 | 37.91 | 33.72 | 0.0447 | 18.86 | 0.0464 | 16.48 |
| **All** | 10.58 | 100 | 100 | 0.0939 | 100 | 0.0990 | 100 |

**Table 3B. Inequality indices by subgroups**

To further analyse this question, we have decomposed the Lorenz curves for both groups according to the clustering of municipalities that we have already presented. This allows us to determine the contribution of each subgroup of municipalities to the Lorenz ordinate at each of the cumulative deciles in which the curve has been evaluated. For this purpose we have calculated the ratios $LC_k$, as explained in Section 2, for men and women (see Table 4 and Figures 4A and 4B). Table 5 shows the demographic weight of each subgroup in each of these cumulative deciles. Note here that the last column in each table accumulates 100% of the population and therefore its figures reflect the percentage of the unemployed ($s^{(k)}$) and the demographic weight ($x^{(k)}$), respectively, that each subgroup of municipalities has on the corresponding groups of men and women.[27]

[26] On the contrary, in the smallest municipalities (subgroup 1), internal inequality is higher for men than for women, despite the fact that the female unemployment rate is 4 points above the male rate.
[27] This information can also be seen in the corresponding columns in Table 3B. There might be, however, some small variations in decimals due to the fact that when calculating the Theil indices, municipalities with unemployment equal to zero have been discarded, as already mentioned.

| | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|
| **MEN** | | | | | | | | | | |
| **Subgroup 1** | 28,51 | 17,63 | 13,13 | 9,61 | 8,26 | 7,77 | 7,26 | 7,05 | 6,71 | 9,50 |
| **Subgroup 2** | 39,42 | 30,12 | 26,26 | 19,11 | 17,00 | 16,56 | 16,17 | 16,06 | 15,71 | 18,21 |
| **Subgroup 3** | 25,84 | 27,18 | 31,95 | 26,35 | 26,18 | 26,91 | 28,16 | 28,23 | 27,91 | 26,99 |
| **Subgroup 4** | 6,24 | 6,43 | 8,10 | 6,79 | 6,82 | 8,07 | 7,39 | 9,69 | 9,82 | 9,66 |
| **Subgroup 5** | 0,00 | 18,64 | 20,57 | 38,14 | 41,74 | 40,69 | 41,02 | 38,97 | 39,84 | 35,65 |
| **All** | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| **WOMEN** | | | | | | | | | | |
| **Subgroup 1** | 23,60 | 12,80 | 9,38 | 8,40 | 7,37 | 6,91 | 7,18 | 6,47 | 6,33 | 8,77 |
| **Subgroup 2** | 27,33 | 16,23 | 14,41 | 14,89 | 14,81 | 15,82 | 16,98 | 15,58 | 15,73 | 19,41 |
| **Subgroup 3** | 32,09 | 20,74 | 18,32 | 21,62 | 23,26 | 24,61 | 29,42 | 26,00 | 27,90 | 28,17 |
| **Subgroup 4** | 11,39 | 8,57 | 7,46 | 7,88 | 8,45 | 7,71 | 6,61 | 7,98 | 9,84 | 9,93 |
| **Subgroup 5** | 5,59 | 41,66 | 50,42 | 47,21 | 46,10 | 44,96 | 39,80 | 43,96 | 40,19 | 33,72 |
| **All** | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |

**Table 4. Contribution of each subgroup, $LC_k$, to the overall Lorenz ordinate (in %)**

| | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|
| **MEN** | | | | | | | | | | |
| **Subgroup 1** | 34,40 | 22,20 | 17,00 | 13,13 | 11,32 | 10,43 | 9,69 | 9,24 | 8,76 | 9,61 |
| **Subgroup 2** | 37,4 | 30,60 | 27,27 | 21,13 | 19,02 | 18,37 | 17,81 | 17,53 | 17,13 | 18,10 |
| **Subgroup 3** | 22,7 | 25,45 | 29,97 | 25,80 | 25,78 | 26,48 | 27,50 | 27,66 | 27,51 | 27,19 |
| **Subgroup 4** | 5,4 | 5,85 | 7,40 | 6,53 | 6,62 | 7,62 | 7,17 | 8,76 | 8,91 | 9,06 |
| **Subgroup 5** | 0 | 15,90 | 18,37 | 33,45 | 37,26 | 37,12 | 37,84 | 36,81 | 37,69 | 36,04 |
| **All** | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| **WOMEN** | | | | | | | | | | |
| **Subgroup 1** | 28,60 | 16,60 | 12,23 | 10,68 | 9,38 | 8,68 | 8,63 | 7,99 | 7,72 | 8,52 |
| **Subgroup 2** | 27,1 | 17,35 | 15,27 | 15,45 | 15,30 | 16,00 | 16,77 | 15,88 | 15,93 | 17,37 |
| **Subgroup 3** | 29,4 | 20,70 | 18,43 | 21,18 | 22,60 | 23,75 | 27,34 | 25,36 | 26,61 | 26,91 |
| **Subgroup 4** | 10,5 | 8,40 | 7,47 | 7,88 | 8,32 | 7,75 | 6,96 | 7,85 | 9,01 | 9,36 |
| **Subgroup 5** | 4,4 | 36,95 | 46,57 | 44,83 | 44,38 | 43,80 | 40,27 | 42,93 | 40,72 | 37,84 |
| **All** | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |

**Table 5. Demographic weight of each subgroup by Lorenz deciles (in %)**

First, we can see that the distribution of men and women by municipality size is similar, even though women have a larger presence in larger municipalities (37.8% against 36% for men) and lower relative weight in the smaller ones (8.5% against 9.6%). Second, as could be expected when looking at the demographic structure, large municipalities are those contributing more female and male unemployed. However, a remarkable fact is that the contribution of this subgroup to the total number of unemployed women is substantially lower than its population weight (33.7% against 37.8%). This is also consistent with the previous results from the M-S index, which suggested that in a great number of large municipalities, the proportion of unemployed women is smaller than their demographic weight.[28] In the case

[28] This effect is compensated by the opposite trend in small and mid-sized municipalities (especially subgroups 2 and 3).

of men, however, the differences regarding demographic weight are almost non-existent. Note that additionally, in larger cities they contribute to the total number of the unemployed to a larger extent than women, despite the fact that the male unemployment rate is almost three percentage points below the female rate (see Table 6).

| | Total population | Men | Women |
|---|---|---|---|
| **Subgroup 1** | 8.58 | 6.64 | 10.78 |
| **Subgroup 2** | 9.18 | 6.73 | 11.78 |
| **Subgroup 3** | 8.81 | 6.64 | 11.04 |
| **Subgroup 4** | 9.18 | 7.13 | 11.19 |
| **Subgroup 5** | 8.03 | 6.61 | 9.41 |
| **All** | 8.60 | 6.69 | 10.56 |

**Table 6. Unemployment rates by subgroups**

The information from the decomposition of the Lorenz curve by deciles allows us to take a step forward and analyse what happens in the different points of the distribution. Thus, when taking into account the first decile, that is, the ten percent of the population living in municipalities with the lowest unemployment rates, we see that those municipalities with fewer than 50,000 inhabitants in the working age group (subgroups 1, 2, and 3) have most of the population and the unemployed, both for women and men (but especially for men). In fact, almost 94% of the unemployed men in this decile live in such population centres.[29] However, subgroup 1 contributes with fewer male and female unemployed than would correspond to its demographic weight, which seems to be a hint to the existence of a significant number of very small municipalities with extremely low unemployment rates. On the other hand, in the male case subgroup 5 does not contribute with any unemployed to the first decile, as there are no large municipalities with very low male unemployment rates. However, there are unemployed women in this subgroup in its corresponding decile. This difference must be due to the fact that the threshold for the female unemployment rate for the first decile (6.4%) is higher than the male one (3.9%) and thus the condition when building the Lorenz curve for the former is less demanding. The fact that female unemployment distribution has a higher average than that of their male counterparts could explain this phenomenon. However, discrepancies not only originate in a translation effect of the density function, but also derive from the larger dispersion of female unemployment, which makes it accumulate a larger proportion of the female population in the lower levels of unemployment rates. In any case, let us not forget that in the specific context of large municipalities, their female unemployment rates are lower than those of other municipal subgroups, while for

[29] In the case of women, this percentage is eleven points below, representing 83% of unemployed women.

men, subgroup 5 does not yield especially low values in relative terms, as already stated (see Table 6).[30]

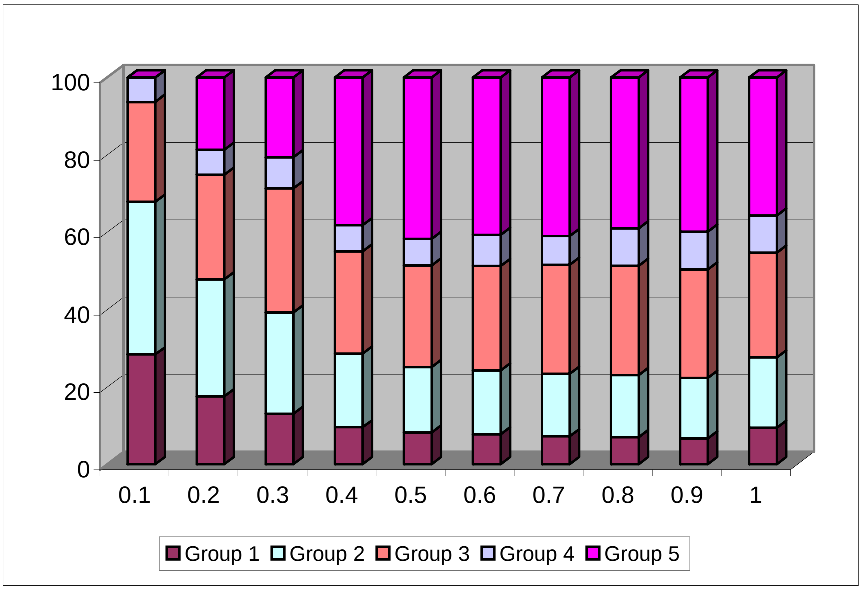


**Figure 4A. Contribution of each subgroup to the overall Lorenz ordinate (%): Men**

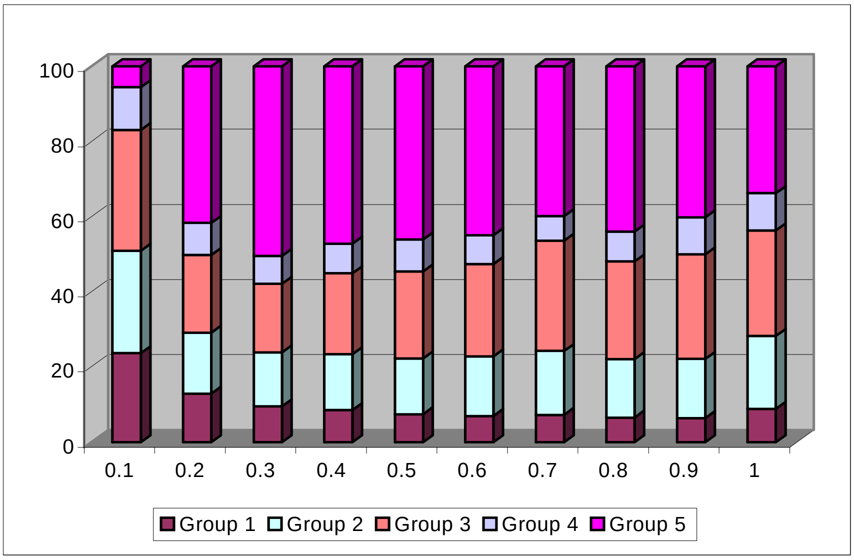


**Figure 4B. Contribution of each subgroup to the overall Lorenz ordinate (%): Women**

Let us now enlarge the scope of our analysis to confirm whether this distributive pattern remains if we consider higher population percentages. Let us take the first three deciles in the male/female distribution; i.e., let us consider 30% of the population living in municipalities

[30] In any case, we should keep in mind that fewer than 1% of the unemployed women in subgroup 5 are in the first population decile, as we will see later.

with the lowest unemployment rates in each distribution. In this case, while the share of the unemployed in the male subgroup 5 scarcely exceeds 20%, the percentage rises to 50% for the female subgroup 5, several points higher than its demographic weight. Thus, the relative weight of large municipalities in the first three deciles is still higher for women than for men, as Figures 4A and 4B show. Therefore, the situation of women in large municipalities seems to be better than that of men, if we compare it to the rest of women living in other municipalities since most of large cities show relatively low female unemployment rates.[31]

The decomposition of the Lorenz curve allows us to look into this issue thanks to the estimation of functions $L(\tau,u^{(k)})$, as previously mentioned in Section 2. These functions indicate how subgroup *k* unemployed are distributed among the cumulative percentiles of the total distribution. Table 7 presents the increase of this function, $L(\tau+0.1,u^{(k)})-L(\tau,u^{(k)})$, in each decile of the male/female distribution for each subgroup of municipalities, while Figures 5A and 5B illustrate the case in the ventiles. In this way we can see the distribution of the unemployed living in each type of municipality by levels of unemployment rates.

| Men | Decile 1 | Decile 2 | Decile 3 | Decile 4 | Decile 5 | Decile 6 | Decile 7 | Decile 8 | Decile 9 | Decile 10 | All |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Subgroup 1** | 13,52 | 6,66 | 5,07 | 1,3 | 3,69 | 5,9 | 5,68 | 7,8 | 7,46 | 42,92 | 100 |
| **Subgroup 2** | 9,74 | 8,25 | 8,38 | 1,15 | 4,94 | 7,7 | 8,39 | 10,38 | 10,81 | 30,26 | 100 |
| **Subgroup 3** | 4,29 | 6,7 | 10,66 | 3,94 | 8,11 | 10,31 | 13,02 | 12,85 | 13,7 | 16,42 | 100 |
| **Subgroup 4** | 2,88 | 4,35 | 8,05 | 3,19 | 6,11 | 12,32 | 4,9 | 25,22 | 15,21 | 17,77 | 100 |
| **Subgroup 5** | 0 | 5,7 | 4,85 | 17,5 | 12,64 | 9,68 | 12,53 | 10,11 | 17,32 | 9,67 | 100 |
| **Women** | | | | | | | | | | | |
| **Subgroup 1** | 12,96 | 3,27 | 2,76 | 5,04 | 3,98 | 5,38 | 9,89 | 4,74 | 9,11 | 42,87 | 100 |
| **Subgroup 2** | 6,8 | 2,48 | 3,85 | 6,14 | 6,2 | 9,09 | 11,61 | 6 | 11,92 | 35,91 | 100 |
| **Subgroup 3** | 5,49 | 2,67 | 3,35 | 7,75 | 8,27 | 9,54 | 18,03 | 4,94 | 18,3 | 21,66 | 100 |
| **Subgroup 4** | 5,54 | 3,98 | 3,77 | 6,63 | 8,46 | 4,51 | 2,23 | 17,12 | 26,02 | 21,74 | 100 |
| **Subgroup 5** | 0,79 | 12,92 | 12,75 | 8,71 | 10,43 | 10,96 | 5,72 | 22,51 | 9,48 | 5,73 | 100 |

**Table 7. Distribution of unemployed in each subgroup by deciles.[32]**

In line with the aforementioned results, large municipalities are once again the subgroup with the lowest proportion of male and female unemployed in the top decile, especially for women. But while in these municipalities almost 26% of their unemployed women are in the second and third decile of the distribution, for men the figures are not relevant until the fourth decile,

[31] Let us note, however, that once again the situation of women remains worse than that of men in large municipalities as well, where unemployment rates are 6.6% for men and 9.4% for women (see Table 6).
[32] These deciles are determined by the construction of the Lorenz curve of distribution *u*.

and show a more even distribution of the unemployed from thereon.[33] All this confirms that, in large cities, there is a lower level of internal inequality for men (as previously shown by the Theil indices), although the proportion of the unemployed men in the last two deciles is significantly higher than that of women (27% against 15%, see Table 7).

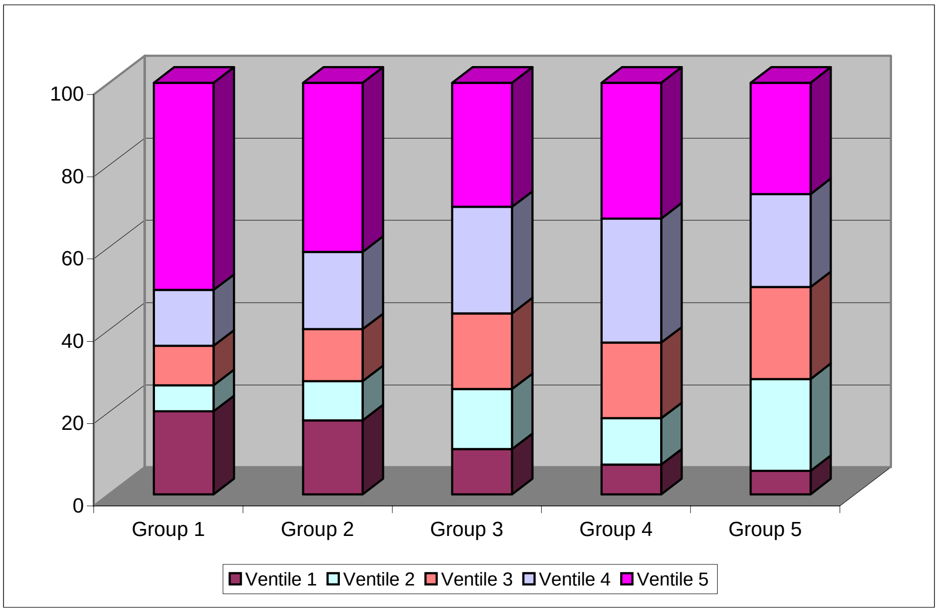


**Figure 5A. Distribution of unemployed in each subgroup by ventiles (%): Men**

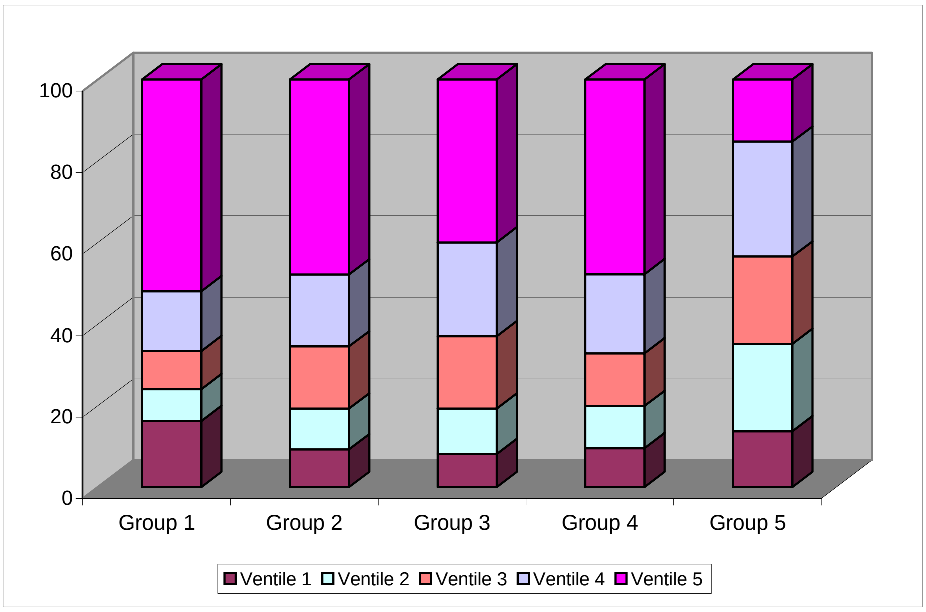


**Figure 5B. Distribution of unemployed in each subgroup by ventiles (%): Women**

[33] Women reach their highest density in the eighth decile at 22.5%.

On the other hand, municipalities with fewer than 2,000 individuals of working age (subgroup 1) show the largest proportion of unemployed women and men in the top decile, with percentages around 43% for both cases. Note that this is also the municipality subgroup with the largest shares of unemployed men and women in the first decile, which explains its high level of internal inequality in the unemployment distribution. On the contrary, subgroup 2, which also accumulates a high percentage in the top decile, has much lower presence in the low tail of the distribution. This is especially true for women,[34] which is reflected in the female unemployment rate in this subgroup--11.8%--the highest of all subgroups. However, for men the unemployment rate in subgroup 2 coincides with the national average, as 18% of their unemployed are in the two first deciles of the distribution.

In the mid-sized subgroups (subgroups 3 and 4), the shares of unemployed women in the top two deciles are significantly higher than those of men, with differences reaching 10 points in each subgroup. Thus, the proportion of the unemployed women living in mid-range municipalities with very high female unemployment rates is remarkably higher than the proportion of male unemployed in the same circumstances. All this leads us to conclude that while large cities seem to offer a particularly favourable situation for female employment, mid-sized population centres are rather unfavourable.

## 4. Conclusions

According to *SPEE* data, women represent 60.7% of the total unemployed population in Spain, and the female unemployment rate, against the total female working age group, is almost four percentage points above the male rate (10.6% against 6.7%). This difference is a fact frequently cited in the literature. Less well-known are the characteristics of the geographical distribution of the unemployed beyond its average regional and provincial unemployment rates. This paper has tried to look into this issue and has thus analysed the spatial concentration of the unemployed population, both men and women, using municipal desegregation, which has enabled us to examine this issue at a more detailed level than in previous studies.

[34] Only 9.3% of its unemployed women live in municipalities with unemployment rates in the first two deciles.

To this end, we have used tools from the literature on income distribution and on economic geography, and we have adapted them to our case in question: unemployment. The use of methodology from economic geography has allowed us to measure the spatial concentration of the unemployed population throughout the Spanish territory. On the other hand, the literature on income distribution has permitted us to analyse better the distributive dimension of this phenomenon. In this vein, this paper not only shows how the unemployed are distributed among the population deciles, ranked according to municipal unemployment rates, but also how the municipal subgroups, classified by size, contribute to the total spatial concentration.

The results highlight that unemployed women are more highly clustered than men, as many of them live in municipalities with extraordinarily high unemployment rates. Thus, around 23% of the unemployed women live in municipalities whose unemployment rates exceed 16% (almost 6 percentage points over the national female average), while only 10% of the male unemployed are in a similar situation (six points over the male national average of 6.7%). Moreover, 10% of unemployed women live in municipalities with rates doubling the national female unemployment rate (22%), while there are hardly any men above that threshold.

When jointly analysing the geographical distribution of both the unemployed and the working age population, we also find a higher spatial concentration of unemployed women, as shown by both the index of economic geography (M-S) and the indices of income distribution. All this means that unemployed men are distributed more consistently with their gender's working age population than are women. In other words, we could state that inequality in the female unemployment distribution is greater than in that of men. In fact, the results of the Theil decomposition analysis show that the contribution of women to total unemployment inequality in Spain almost doubles that of men.

The discrepancies between male and female territorial patterns are partly due to the dissimilar situations of both sexes in the different municipality subgroups. Thus, in large cities, the percentage of unemployed women is significantly lower to their demographic weight, while in the case of males there are hardly any differences. On the other hand, within these municipalities, there is a higher level of inequality in female than in male unemployment.[35]

[35] Although in any case they are much lower than those of other population centres. In fact, the highest internal inequality levels are always in small municipalities.

The explanation for this phenomenon is found in the different decile shares of male and female unemployment. Thus, 26.5% of unemployed women living in large cities are in the first three deciles of their distribution, while this ratio only reaches 10.5% for men. However, in the top two deciles, large cities account for around 27% of their unemployed men and only 15% of their unemployed women. Perhaps this is the reason why the female unemployment rate in large municipalities, despite the fact that it is high at 9.4%, is lower than in other subgroups of municipalities, where rates are around 11%. On the contrary, such municipalities do not seem to show an advantageous position for men, as they show a male unemployment rate that is almost identical to the national average. Therefore, we can claim that unemployment is not especially intense in large cities, and that the situation seems to favour women living there in comparison to the remaining female population.

Municipalities belonging to subgroups 2, 3 and 4 show, on the contrary, a completely different situation.[36] In this case, their unemployment rates are higher than the national average (especially for women). Furthermore, as the M-S index shows, unemployment is more spatially concentrated here than in other subgroups. This means that within these subgroups, municipalities with higher unemployment rates have an important demographic weight, especially in the case of women. On the other hand, these municipalities also show a larger proportion of unemployed women than men in the last two deciles, which contributes to explaining the major differential between the two unemployment rates.

All these facts lead to the final conclusion of this paper: there are significant differences in the spatial distribution of male and female unemployment in Spain, and employment opportunities for women in mid-sized municipalities (subgroups 2, 3, and 4) are worse than those in large municipalities. For men, however, larger municipalities do not seem to be especially advantageous places if we compare them with the remaining subgroups. Therefore, the decomposition of municipalities by size is not relevant when trying to explain the existing inequality in male unemployment rates. On the contrary, the different pattern of female unemployment in large cities does indeed make the size variable an explanatory factor of total female inequality, beyond the inequality proper to each one of the municipal subgroups.

[36] Here we leave the smallest municipalities (subgroup 1) aside as their unemployment rates are around the national average both for men and for women. However, note that due to their high internal inequality, unemployment rates in those municipalities greatly differ from each other.

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