The geographical concentration of unemployment:

A male-female comparison in Spain*

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Abstract

The aim of this paper is to analyse gender differences in the spatial distribution of unemployment when taking into account the size of the municipality where the unemployed live. Specifically, using data from Spain, we explore the spatial concentration patterns of male and female unemployed by using tools from the literature on economic geography and income distribution. As opposed to previous works, the territorial scale considered is the municipality rather than the province or region, which allows us to show gender differences between large cities and small towns.

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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. In this vein, Overman and Puga (2002) analyse unemployment clusters in Europe to determine the importance of the transnational and regional dimension in the creation of such clusters.[1]

The spatial dimension of the labour market has not been, however, widely studied in the literature, where efforts have been oriented towards evidencing and explaining differences among countries or regions but not at a finer geographical scale, which prevents any analysis of the effects of agglomeration on the labour market. Exceptions to this trend are Wheaton and Lewis (2002) and Glaeser and Maré (2001), who find evidence of increasing urban wages caused by various types of externalities, such as labour specialization and learning spillovers in urban areas. However, there has been little consideration of whether male and female workers benefit from this premium at the same level. Phimister (2005) explores these differences in the United Kingdom labour market and suggests larger urban wage premiums for women and also a significant urban participation premium for women, but none for men. However, this paper does not examine the effects of city size in depth since only a broad rural-urban categorization is considered.

[1] While Overman and Puga (2002) emphasize that neighbour effects have a transnational dimension, Meliciani (2006) suggests that national factors and the negative performance of Objective 1 regions are more important than neighbour effects to explain polarization of employment in Europe.

The aim of this paper is to analyse gender differences in the spatial distribution of unemployment when taking into account the size of the municipality where the unemployed live. Specifically, using data from Spain, we explore the spatial concentration patterns of male and female unemployed by using tools from the literature on economic geography and income distribution. As opposed to previous works, the territorial scale considered is the municipality rather than the province or region, which allows us to show gender differences between large cities and small towns.[2]

In keeping with our purposes, we first follow the index of spatial concentration proposed by Johnston *et al.* (2003) to analyse to what extent individuals of a target group (unemployed) are located in areas with other members of that group. Second, we use the Maurel and Sédillot (1999) index, which was initially proposed to analyse the geographic concentration of industries in France. 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. For a deeper analysis of distributive aspects, this paper follows the literature on income distribution (the Lorenz curve and the Gini and Theil indices).[3] In this vein, we 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 unemployment distribution. The decomposition of the Theil index is also used to determine the contribution of men and women to the overall concentration of unemployment. These empirical

[2] López-Bazo *et al.* (2002, 2005) analyse other spatial aspects of the distribution of unemployment in Spain to explain the evolution of differences in unemployment rates at a 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.

[3] 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).

procedures, which come from diverse traditions and focus on different aspects of the distribution, will bring more robustness to the results.

The study of gender gaps in unemployment rates is not just an important issue from an egalitarian point of view. In line with the Lisbon Strategy on growth and employment, the Council of the European Union (EU) recommends the Member States to implement policies to "contribute to achieving an average employment rate for the EU of 70% overall, of at least 60% for women […] by 2010" (EC, 2005, p. 24). However, these objectives are far from being reached in the Mediterranean countries, where not only the unemployment rates but also the gender gaps in unemployment rates are remarkably high. In fact, according to a recent OECD (2004) report, in Spain the female unemployment rate was 16% in 2003, while the male unemployment rate was 8.2%.[4] However, despite these important differences, national rates do not enable us to find out the gender discrepancies at other territorial scales. This is a relevant matter since unemployment rates usually show important domestic disparities across regions.[5] Therefore, the spatial analysis of gender differences in unemployment should have an increased weight, not only for its academic interest, but also for its potential role on the design of area-based public policies aimed at improving competitiveness and reducing 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 concentration of male and female unemployment in Spain. The main conclusions are introduced in Section 4.

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[4] If these data are compared with those of the overall EU the situation looks even worse, since the female rate was 8.6% (almost half the Spanish figure), and the male rate 7.2% (just one point less).

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

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 use methodologies developed both from the literature on economic geography and that from income distribution, and we adapt them to our case study.

- ***Economic Geography***

First, we use a graphic procedure, proposed by Johnston *et al.* (2003), to analyse the location of the unemployed against that of other unemployed. In fact, this concentration profile provides information about the percentage of unemployed (against the total number of unemployed) living in locations with unemployment rates above any given threshold.[6] It should be mentioned that this curve is not affected by changes in the population size of municipalities with unemployment rates equal to zero, since these areas do not participate in the unemployment distribution.

Second, we analyse whether the distribution of the unemployed among locations is closely related to the distribution of the population as a whole. This means that we focus on "relative concentration," since we measure the degree to which unemployed are concentrated relative to the geographical distribution of the overall population. For this purpose, we use the concentration index initially proposed by Maurel and Sédillot (1999) (M-S) to measure industrial concentration, which can be reinterpreted as follows:[7]

[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 figures of unemployed living in municipalities with rates above that threshold.

[7] 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.

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

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

As opposed to Johnston *et al.* (2003), this index estimates the discrepancies between the distribution of the unemployed and that of the reference population, considering the whole set of locations, including those with no unemployment. Note that the M-S index is quite sensitive to the size of the municipalities where the unemployed live. In fact, the *C*'s numerator can be written as follows: $\sum_i (s_i - x_i)(s_i + x_i)$ and thus, if in a municipality the unemployed share (s_i) is larger than the population share (x_i), the difference will be positive. *Ceteris paribus,* the higher the population size in that location, the greater influence it will have on the index. This means that the index depends on the distribution of the population across locations. If the whole population were only in one location, its value would differ

[8] In our case, index γ 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.

from that reached if the population were uniformly distributed between several locations. This does not occur, however, with inequality indices, which are invariant to the territorial scale.

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 approach the literature on income distribution. In order to construct the Lorenz curve of unemployment, the different municipalities are lined up in ascending order of the ratio $\left(\frac{s_i}{x_i}\right)$. This quotient equals the unemployment rate at *i* divided by the unemployment rate of the whole 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. We can think of this curve in terms of the cumulative share of the unemployed or the cumulative share of unemployment rates (weighted by population size). 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 municipal unemployment rates.[9]

[9] Let us note that the 45 degree line represents the situation 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 Lorenz curve can be decomposed using different population subgroups (in our case, municipal subgroups designed according to their size). More precisely, according to Bishop *et al*. (2003), we can write:

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

where $L(\tau,u)$ represents the Lorenz curve of the *u* distribution in the percentile τ (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 τ of the total distribution (*u*). Let us note that functions $L(\tau,u^{(k)})$ are not the Lorenz curves of each subgroup, since they do not represent the cumulative percentage of the unemployed in that subgroup until reaching its own percentile, $\tau^{(k)}$, but until the total population percentile, τ.

This decomposition is of great interest, as it allows us to go further in the analysis. 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 $L(\tau,u^{(k)})$ enables us to determine how the unemployed of subgroup *k* are distributed among the percentiles of the whole distribution. In particular, for subgroup *k*, expression $L(\tau + 0.1,u^{(k)}) - L(\tau,u^{(k)})$ indicates the proportion of unemployed in each decile τ.

When the Lorenz criterion is not conclusive, since there are intersections between the curves of two distributions, we can use complete indices. 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:

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

where $\bar{u}_i = \frac{n_i}{p_i}$ is the unemployment rate of municipality *i*, and $\overline{U} = \frac{N}{P}$ the unemployment rate in the economy as a whole. The Theil indices are other inequality indicators we use in the empirical analysis. The expressions of these indices in our case are:

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

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

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

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

An advantage of this family of indices is that its members can be decomposed. In this regard, the literature on inequality has focused on characterising two types of decomposition:

i) **Inequality decomposition by subpopulations.** By using this decomposition, we can analyse whether the classification by municipality size is an important dimension in the phenomenon of unemployment concentration. Decompositions derived from Theil indices, with parameters 0 and 1, can be expressed as follows:

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

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

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.

ii) **Inequality decomposition by factor components.** In order to analyse the differences between male and female spatial patterns, we decompose the total unemployed population of each municipality into unemployed men and women. The symbol u_c represents the distribution resulting from dividing, in each location, the number of unemployed in the group c (men or women) by its total population size, and u is the distribution of municipal unemployment rates. 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:[10]

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

where the subindex c represents the male (m) or female (f) component of unemployment and ρ_c is the correlation coefficient between distributions u and u_c. T_{2c} is the Theil index, with parameter 2, applied to distribution u_c, and $\overline{u}_c$ is the average of such distribution (weighted by municipality size).

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

3. Comparisons between male and female unemployment

3.1. Data sources

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 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 service, *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. 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, which have been recently set up to improve the management of active employment policies (Toharia and Malo, 2005).

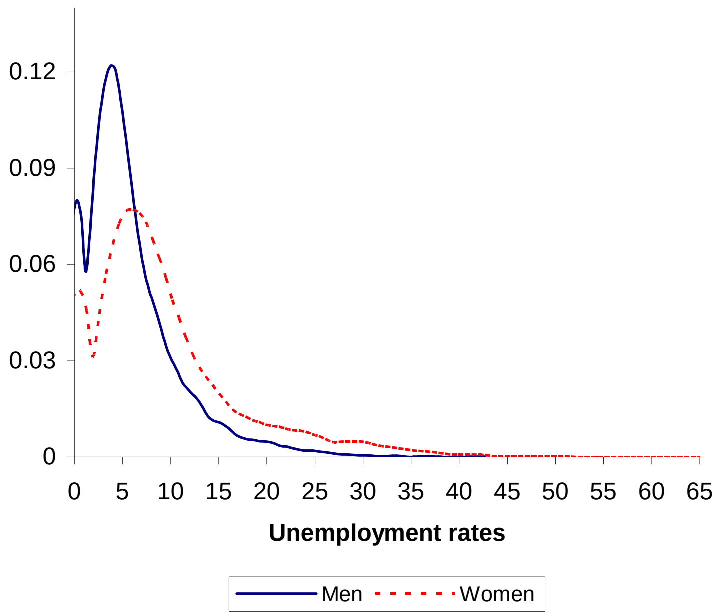
As we do not have access to data about the economically active at the municipal level, the unemployment rate has been calculated by dividing the number of the unemployed, according to the DENOs concept, by the working age population (which in Spain is the group aged 16 to

64 years). 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.[11]

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 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 female unemployment rate weighted by municipality size is 10.6%, and the simple average is 9%, while for men the average is 6.7% in the first case and 5.7% in the second.[12] The difference between the weighted and the

[11] 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.

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

simple average 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.[13]

We now build the concentration profile curve, which yields information on the proportion of the unemployed living in 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).

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

Second, we gather the unemployed population above each threshold. In this way, as shown in the third column, almost 48% of the unemployed women live in municipalities with rates over 12% (a point above their average). On the other hand, we also note that only 3% of the female

[13] The standard deviation is 5.1 for women and 2.9 for men (7.8 and 5, respectively, in the unweighted distributions).

unemployed are in municipalities with rates below (or equal to) 6%. The information of this 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.

If we compare these curves for men and women, many differences become evident (Figure 2).

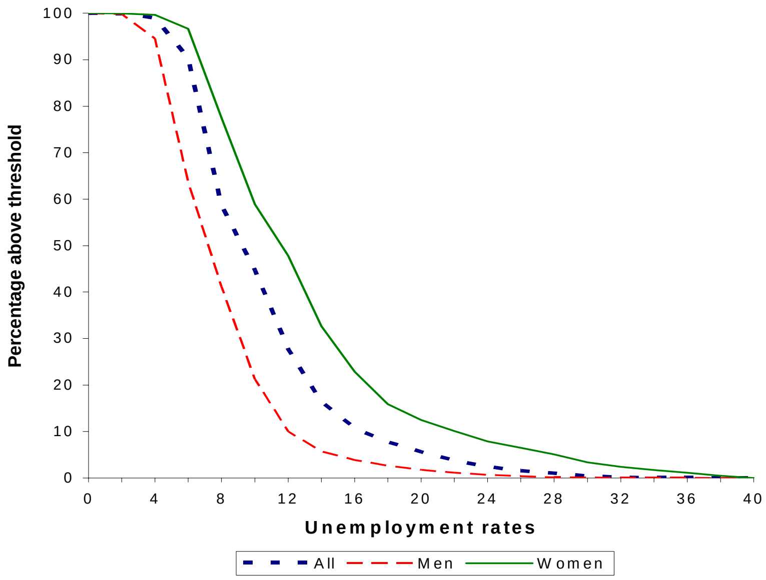


Figure 2. Concentration profile curves

Thus, while around 23% of the unemployed women live 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 unemployed women are more clustered in space than men, i.e., many of them live in municipalities with extremely high female unemployment rates.

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 is 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 unemployed share 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 between the distributions of male and female unemployment. Thus, even if the M-S index is below zero in both cases, for the female unemployment the (absolute) value doubles that of men (see Table 2, last row). This index becomes negative if there are many municipalities with a proportion of unemployed below the demographic weight, and especially if this happens in larger municipalities. The result suggests that this situation is more prevalent for female 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 aged 16 to 64 (subgroup 1), those having between 2,000 and 10,000 (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 municipalities unemployment is not particularly intense, although the situation seems to be 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.[14]

	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

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 the Lorenz curve.

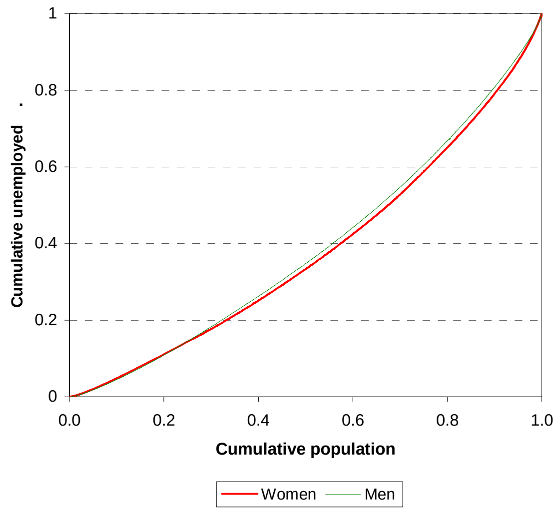


Figure 3. Unemployment Lorenz curves

Figure 3 shows that the Lorenz curve for unemployed women is below that of men after the third decile, while in the first two deciles the opposite holds (although with almost

[14] The fact that the M-S index has higher absolute values 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.

insignificant differences between them).[15] 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. 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 in the case of female unemployment are also higher than those attained in the male case.[16] Thus, we can state that unemployed women are more geographically concentrated than men.

When using the factorial decomposition of the Theil 2 index, we see that women contribute more 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 (see Table 3).

	Unemployed (%)	**Theil -1**	**Theil 0**	**Theil 1**	**Theil 2**	**Theil 2 decomposition by sex (%)**	**Theil 0 decomposition by municipality size W – B (%)**	**Theil 1 decomposition by municipality size 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 3. Theil indices

[15] Since we do not work with a sample but with the whole population of unemployed, statistical inference cannot be applied.
[16] In order to calculate these indices, those municipalities with an unemployment rate equal to zero have to be discarded, as some of those indicators are not defined for such a value.

The decomposition of Theil 0 and Theil 1 by municipality size shows that the size variable is a relatively important dimension in the phenomenon of female unemployment concentration since it enables us to explain about 4% of the total female inequality (Table 3). However, in the case of men, its contribution is practically non-existent. This is due to the fact that the average male unemployment rates do not show any remarkable differences among the different municipalities subgroups, while for large cities the female unemployment rate is clearly below the level reached in the remaining municipalities (see Table 4).[17]

	Unemployment rates			Theil 1	
	All	**Men**	**Women**	**Men**	**Women**
Subgroup 1	8.58	6.64	10.78	0.24	0.23
Subgroup 2	9.18	6.73	11.78	0.13	0.14
Subgroup 3	8.81	6.64	11.04	0.06	0.09
Subgroup 4	9.18	7.13	11.19	0.05	0.07
Subgroup 5	8.03	6.61	9.41	0.04	0.05
All	8.60	6.69	10.56	0.08	0.10

Table 4. Unemployment rates and inequality by subgroups

To further analyse this question, we have decomposed the Lorenz curves by the above subgroups. 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 5 and Figures 4A and 4B). Table 6 shows the demographic weight of each subgroup in each of these cumulative deciles. Note here that the last column in Tables 5 and 6 accumulates 100% of their populations, and therefore shows 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.

[17] Table 4 also shows that the smallest municipalities (subgroups 1 and 2) have much higher inequality levels of unemployment than mid-sized and large municipalities, both for women and men.

	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 5. 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 6. 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 smallest (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 subgroup 5 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 was smaller than their demographic weight. In the case of men, however, these differences are negligible.

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 individuals (subgroups 1, 2, and 3) have most of the population and the unemployed, both for women and men (but especially for men).

We now consider the first three deciles in the male/female distribution; i.e., the 30% of the population living in municipalities with the lowest unemployment rates. We observe that while the share of unemployed men belonging to subgroup 5 scarcely exceeds 20%, this percentage rises to 50% in the female case. Thus, the relative weight of large municipalities in the first three deciles is much higher for women than for men, as Figures 4A and 4B show.

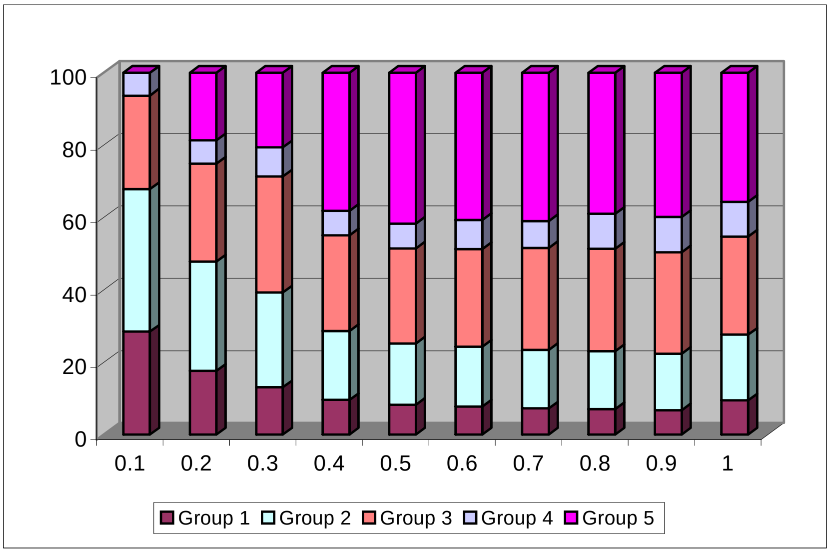


Figure 4A. Contribution of each subgroup to the overall Lorenz ordinate (%): Men

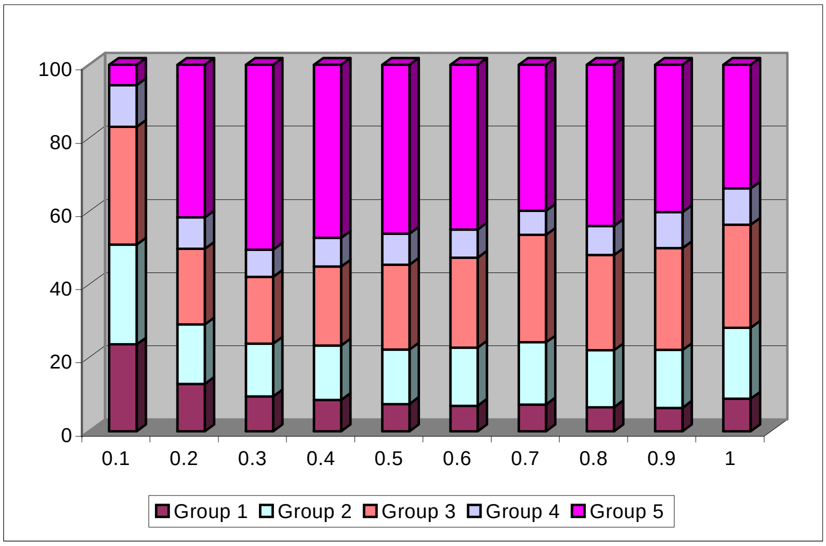


Figure 4B. Contribution of each subgroup to the overall Lorenz ordinate (%): Women

Next, we study how the unemployed of each municipality subgroup are distributed among the deciles of the total distribution, given by expression $L(\tau+0.1,u^{(k)})-L(\tau,u^{(k)})$ (Table 7).

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.[18]

Large municipalities is the subgroup with the lowest proportion of male and female unemployed in the top decile, especially for women. However, while in these municipalities almost 26% of unemployed women are in the first three deciles of the distribution, for men the figures are not relevant until the fourth decile. The lower level of male internal inequality

[18] These deciles are determined by the construction of the Lorenz curve of distribution *u*.

does not alter the fact that the proportion of the unemployed men in the last two deciles is significantly higher than that of women (27% against 15%, see Table 7).

Municipalities with fewer than 2,000 individuals (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 subgroup with the largest shares of unemployed men and women in the first decile, which is consistent with its high inequality level (Table 4). 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, and it explains why the female unemployment rate in this subgroup is the highest (Table 4). However, the unemployment male rate in subgroup 2 coincides with the national male average, as the proportion of unemployed men in the three first deciles of the distribution is larger.

In 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 unemployed women living in mid-sized municipalities with very high female unemployment rates is remarkably higher than that of men. 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 the public employment services, women represent 60.7% of the total unemployed population in Spain, and the female unemployment rate is almost four percentage points above the male rate.[19] 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 analysed the spatial concentration of the unemployed population, both men and women, at the municipality scale, which has enabled us to examine this issue at a more detailed level than in previous studies. 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.

The concentration profile curves show that unemployed women are more highly clustered than men, as many of them live in municipalities with extraordinarily high unemployment rates. Inequality in the female unemployment distribution is also greater. In particular, the Theil decomposition shows that the contribution of women to the overall unemployment inequality/concentration almost doubles that of men.

These spatial discrepancies are the consequence of the different situations of men and women, depending on the size of the municipality where they live. The smallest municipalities (subgroup 1) have the highest level of dispersion in unemployment rates, with a large share of the unemployed living in municipalities with the highest unemployment rates of the country, but they do not show important gender differences. Municipalities of subgroups 2, 3 and 4 are the ones with the highest unemployment rates, especially for women. Moreover, these municipalities have important gender gaps, since the proportion of unemployed women in the last ventile of the distribution is several percentage points higher than that of men. On the contrary, large municipalities (subgroup 5) not only have the lowest unemployment rate, but also show a lower spatial concentration (as suggested by both the distributive analysis and the

[19] The unemployment rates are 10.6% and 6.7% for women and men, respectively. Remember that these rates are the quotient between the number of unemployed and the number of persons aged 16 to 64 years.

M-S index). In other words, unemployment is not especially intense in large cities. However, the advantage of living in these cities does not affect women and men equally. The analysis suggests that this situation seems to favour especially the female population. In particular, the unemployment gap between large cities and the remaining locations, both taking into account the average and the whole distribution, is higher for women.

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 makes indeed the size variable an explanatory factor of total female inequality, beyond the own inequality of each of these subgroups. These results are in line with Phimister (2005), who finds a significant urban participation premium for women but not for men. However, our results suggest that the female employment premium only appears in municipalities of a certain size, since large and mid-sized cities do not have the same behaviour.

It is not so obvious why in some countries women, once they enter the labour market, have a lower probability of finding a job than men. The explanations to this fact are complex and there is little recent literature on this topic. Azmat *et al.* (2006) point out that gender gaps in unemployment rates in OECD countries can be partially explained by differences in human capital accumulation interacted with labour market institutions. They also suggest that prejudice against women can play a role in countries with high unemployment rates. However, the spatial dimension has not been taken into account in their analysis.

Our paper gives evidence that the size of the municipality where unemployed live can be a relevant variable to explaining gender differences. There can be a number of reasons to explain this fact: learning spillover effects, job matching, discriminatory behaviour, and childcare facilities may depend on the city size. Future research should analyse whether agglomeration is also a relevant issue in other countries with high gender gaps in unemployment rates, and explore what factors may explain the relative advantage of large cities for women.

References

Amiti M. (1999) "Specialization patterns in Europe", *Weltwirtschaftliches Archiv* **135(4),** 573-593.

Azmat G., Güell M. and Manning A. (2006) “Gender gaps in unemployment rates in OECD countries”, *Journal of Labor Economics* **24(1)**, 1-37.

Bishop J., Chow V. and Zeager L. (2003) “Decomposing Lorenz and concentration curves”, *International Economic Review* **44(3),** 965-978.

Brülhart M. and Traeger R. (2005) “An account of geographic concentration patterns in Europe”, *Regional Science and Urban Economics* **35(6)**, 597-624.

Combes P.-F. and Overman H. (2004) “The spatial distribution of economic activities in the EU”, in Henderson J.V. and Thisse J.-F. (Eds) *Handbook of Urban and Regional Economic 4*. North-Holland, Amsterdam.

European Council (2005) “Guidelines for the employment policies of the Member States”, http://europa.eu.int/comm/employment_social/employment_strategy/prop_2005/adopted_guidelines_2005_en.htm

Glaeser E. and Maré D. (2001) “Cities and skills”, *Journal of Labor Economics* **19**, 316-342.

Johnston R., Voas D. and Poulsen M. (2003) “Measuring spatial concentration: the use of threshold profiles”, *Environment and Planning B: Planning and Design* **30**, 3-14.

Kim S. (1995) “Expansion of markets and the geographic distribution of economic activities: the trends in U.S. regional manufacturing structure, 1860-1987”, *The Quarterly Journal of Economics* **110(4),** 881-908.

López-Bazo E. del Barrio T. and Artis M. (2002) "The regional distribution of Spanish unemployment: a spatial analysis", *Papers in Regional Science* **81,** 365-389.

López-Bazo E. del Barrio T. and Artis M. (2005) "Geographical distribution of unemployment in Spain", *Regional Studies* **39(3),** 305-318.

Maurel F. and Sédillot B. (1999) "A measure of the geographic concentration in French manufacturing industries", *Regional Science and Urban Economics* **29,** 575-604.

Meliciani V. (2006) "Income and employment disparities across European regions: The role of national and spatial factors", *Regional Studies* **40 (1)**, 75-91.

OECD (2004) *Employment Outlook, Statistical Annex* pp. 291-327.

Overman H. and Puga D. (2002) "Regional unemployment clusters", *Economic Policy*, April, 116-147.

Phimister, E. (2005) "Urban effects on participation and wages: Are there gender differences", *Journal of Urban Economics* **58**, 513-536.

Quadrado L., Former H. and Loman S. (2001) "Regional inequality in the provision of health care in Spain", *Environment and Planning A* **33(5),** 783-794.

Shorrocks A. (1980) "The class of additively decomposable inequality measures", *Econometrica* **48,** 613-625.

Toharia L. (2003) "El mercado de trabajo en España", *Información Comercial Española* **811,** 203-220.

Toharia L. (2005) “El desempleo en España”, in Navarro V. (Ed.) *La Situación Social en España*. Fundación Largo Caballero y Biblioteca Nueva, Madrid-Barcelona.

Toharia L. and Malo M. A. (2005) “La influencia de la implantación del SISPE en el paro registrado”, http://www.inem.es/cifras/p_datbas.html.

Wheaton, W. C. and Lewis, M. J. (2002) “Urban wages and labor market agglomeration”, *Journal of Urban Economics* **51**, 542-562.