

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. As opposed to previous works, here the territorial scale is the municipality rather than the province or region, which allows us to show gender differences in unemployment rates between large cities and small towns. Using data from Spain, we explore this issue by using tools from the literature on economic geography and income distribution, and we adapt these measures to our case.

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Keywords: Spatial Concentration; Unemployment; Gender; Municipality Scale

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1. Introduction

In the literature on economic geography there is a wide consensus regarding the relevance of agglomeration patterns of economic activities. In this respect, many theoretical and empirical papers have been written looking into this aspect of spatial analysis (Combes and Overman, 2004). 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 (Overman and Puga, 2002; Meliciani, 2006).

The spatial dimension of the labour market has not been widely studied in the literature, however, where efforts have been oriented towards evidencing and explaining differences among countries or regions but not at a finer geographical scale. Exceptions to this trend are Wheaton and Lewis (2002), Glaeser and Maré (2001), and Yankow (2006), who find evidence of advantages for workers in urban areas caused by various types of externalities. However, there has been little consideration of whether male and female workers benefit from urban advantages at the same level. Phimister (2005) explores this issue 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.

On the other hand, literature on gender gaps has focused mainly on pay and participation differentials, whereas gender gaps in unemployment rates have received much less attention in recent years. An exception is the paper by Azmat *et al.* (2006), which investigates gender gaps in unemployment rates between OECD countries. However, their analysis is undertaken at a nationwide aggregate level, so that inner differences, and in particular the effect of agglomeration, are not considered.

The study of gender gaps in unemployment rates is an important issue not only from an egalitarian point of view. In line with the Lisbon Strategy on growth and employment, the Council of the European Union (EU) recommends that Member States 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%. However, despite these important differences, national rates do not enable us to determine gender discrepancies at other territorial scales. This is a relevant matter since unemployment rates usually show important domestic disparities across regions.¹ 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 in the design of area-based public policies aimed at improving competitiveness and reducing inequalities between men and women in the labour market.

The aim of this paper is to analyse gender differences in the spatial distribution of unemployment while taking into account the size of the municipality where the unemployed live.² As mentioned above, the rural-urban dimension seems to be an important variable in analysis of gender differences in wages and participation rates. Specifically, using data from Spain, we explore whether agglomeration can also influence gender gaps in unemployment rates. In doing so, we use tools from the literature on economic geography and income

¹ 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 López-Bazo *et al.* (2005) analyse other spatial aspects of the distribution of unemployment in Spain at a provincial level, while Toharia (2003; 2005), amongst others, focuses on regional differences.

distribution. All these empirical procedures complement each other, since they allow us to highlight different aspects of the unemployment distribution.

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 (M-S), which was initially proposed to analyse the geographic concentration of industries, and reinterpret it in order to measure unemployment concentration. 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. This means that we focus on “relative concentration,” since we measure the degree to which the unemployed are concentrated relative to the geographical distribution of the overall population. And finally, this paper follows the literature on income distribution (the Lorenz curve and the Gini and Theil indices) and adapts these procedures to our case.³ These tools also permit us to quantify the differences between the distribution of the unemployed and that of the overall population, but paying more attention instead to the relative severity of unemployment in each municipality. As will be shown, these measures also bring us helpful decompositions of the overall concentration by subgroups of municipalities and by gender.

The paper is structured as follows: Section 2 presents the various mechanisms through which gender differences in the labour market may arise, paying especial attention to gender gaps in urban contexts. Section 3 gives a detailed explanation of the methodologies that will be used

³ Some of these indices have been used not only 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 (Brühlhart and Traeger, 2005).

in Section 4 for an analysis of the spatial concentration of male and female unemployment in Spain. The main conclusions are introduced in Section 5.

2. Background

Apart from discrimination, male-female differences in labour market outcomes may arise for several reasons (see Altonji and Blank, 1999 for a revision of this literature). Gender gaps in wages, occupations, and employment patterns can be the consequence of differences in skills and preferences—individuals may differ in their preferences for jobs, market versus non-market work, etc. The source of these differences is not, however, so clear, since preferences and skills can be shaped by pre-market discrimination, as a result of differences in treatment between boys and girls, and also by future expectations. Women who expect to spend an important part of their lives in childcare will be less likely to invest in human capital, and those who expect to face barriers against entering certain occupations will invest in skills oriented mainly towards traditionally female jobs. On the other hand, skills depend not only on pre-market human capital, but also on experience, which points to another possible explanation of gender differences in the labour market. Those individuals who work fewer hours and/or fewer years in the course of their careers, as some women do in order to take care of children, are expected to have lower investments in training, and as a consequence, lower accumulation of and returns to experience. It follows then that family characteristics, such as marital status and the number of young children, and also social roles can be important variables affecting female labour decisions and, therefore, they help to explain gender differences in the labour market.

The above literature has focused mainly on pay differentials and participation rates, and more recently on occupational segregation,⁴ while other aspects of the labour market, such as gender gaps in unemployment rates, have received much less attention. This latter issue was initially addressed by works of the 70s and 80s concerned about the high unemployment rate differential between men and women in the U.S. during the post-war period (Niemi, 1974; Seeborg and DeBoer, 1987). However, there is little recent literature on the topic, in spite of the remarkable gender gaps in unemployment rates of some European countries, in particular the Mediterranean countries, where the unemployment problem is mainly a problem of female unemployment (see Table 1).

| Unemployment rates (2003) | Women | Men |
|----------------------------------|--------------|------------|
| Austria | 4.3 | 5.1 |
| Belgium | 8.0 | 7.5 |
| Denmark | 5.8 | 5.2 |
| Finland | 8.9 | 9.3 |
| France | 10.4 | 8.3 |
| Germany | 8.9 | 9.7 |
| Greece | 13.8 | 5.9 |
| Ireland | 3.9 | 4.9 |
| Italy | 11.7 | 6.8 |
| Luxembourg (2002) | 3.6 | 1.9 |
| Netherlands | 3.8 | 3.5 |
| Portugal | 7.7 | 5.9 |
| Spain | 16.0 | 8.2 |
| Sweden | 5.3 | 6.4 |
| United Kingdom | 4.1 | 5.5 |
| EU-15 | 8.6 | 7.2 |

Source: OECD (2004) report

Table 1. Unemployment rates in E.U. countries.

An exception to this trend is the paper by Azmat *et al.* (2006), which analyses gender differences in unemployment rates between OECD countries. They find that high-gap countries tend to have larger gender gaps in flows from employment to unemployment (and vice versa), even though domestic responsibilities do not seem to have a big influence on

⁴See Blau and Kahn (2003), Anker (1998), Dolado *et al.* (2002), and Petrongolo (2004), among others.

these transitions (women with children are more likely to leave employment for inactivity than for unemployment). They also suggest that differences in human capital accumulation and labour market institutions can help to explain a large part, but not all, of the gender gap in unemployment rates.⁵ Social attitudes toward male and female employment can also be determinants of the gap in countries with high unemployment rates. In this vein, Petrongolo (2004) shows evidence of female over-representation in part-time and temporary jobs (what she calls “atypical” jobs) in most countries of the EU and suggests the existence of discrimination in Southern Europe since this segregation is not well explained by differences in preferences or productivities.

The aforementioned papers investigate gender differences at nationwide levels, so that inner differences within countries are not considered in their analyses. However, countries are not homogeneous geographical units, but instead usually experience important regional disparities. A recent strand of the literature on urban economics analyses how agglomeration influences labour market outcomes. In this regard, Wheaton and Lewis (2002) find evidence of willingness of firms to pay higher wages in dense areas as a consequence of agglomeration economies in urban markets. Glaeser and Maré (2001) explain this urban premium instead by knowledge spillovers—since cities favour the accumulation of human capital—and Yankow (2006) suggests that not only the learning hypothesis, but also the coordination hypothesis—which focuses on the matching between workers and firms—can help to explain the urban wage premium. However, there is little evidence as to whether agglomeration affects women and men differently. An exception is the recent paper by Phimister (2005) which explores gender differences in both urban wage and participation premiums in the U.K. There may be a number of reasons for these differences. First, denser urban labour markets may favour the

⁵ Bazen (2003) documents that only a third of the gender gap in unemployment rates in France can be explained by differences in characteristics.

job matching of individuals of lower geographical mobility. Second, urban areas may also facilitate the job matching of individuals with more interrupted careers. All this suggests that urban areas may be particularly beneficial for women because of their lower spatial mobility and higher job turnover rate. And third, urban areas allow greater childcare provision and transportation, which should also increase female participation rates. Phimister (2005) presents evidence of a significant urban participation premium for women (especially for those married or cohabitating) but not for men, even though the source of this premium is not determined. With respect to wages, he also finds gender differences (since the urban premium is larger for women) and suggests that the job matching hypothesis plays a more important role in explaining this fact than learning spillover effects.⁶

Since the rural-urban dimension seems to be an important variable in an analysis of gender differences in wages and participation rates, it would be interesting to determine whether agglomeration can also influence gender gaps in unemployment rates, as we explore in this paper.

3. Methodology

We use methodologies developed from the literature on economic geography and income distribution, and we adapt them to our case study. First, we present a graphical procedure, proposed by Johnston *et al.* (2003), to approach the spatial differences between the distributions of male and female unemployed. Next, the M-S index and the income distribution tools are shown. These procedures permit us to compare the distribution of the unemployed with that of a given population of reference (which for us will be the people in

⁶ Di Addario (2006) also finds evidence that agglomeration (positively) affects the matching process in Italy, especially for women. In particular, the influence of agglomeration on individuals' chances of finding a job is larger for women.

the working age group) to determine gender gaps. However, even though both approaches focus on relative concentration, they differ in the way the differences between the unemployment and population distributions are taken into account. In this vein, while the latter are neutral against changes in the distribution of the population across locations, the former is not, since what happens in larger municipalities has a greater effect on the index. On the other hand, income distribution tools pay more attention to the relative severity of the problem. In this respect, when aggregating these differences, they take into account the relative position of each municipality in terms of unemployment rates. The two types of measures seem reasonable and focus on different aspects of the distribution, so we have chosen to use both in the empirical section. Finally, we use the decomposition of the Lorenz curve by subgroups, 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.

- ***Measuring concentration with economic geography indices***

First, we use a graphic procedure, proposed by Johnston *et al.* (2003), to analyse how clustered the unemployed are. In particular, the concentration profile curve provides information about the percentage of unemployed (against the total number of unemployed) living in locations with unemployment rates above any given threshold.⁷ 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.

⁷ 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.

Second, we analyse whether the distribution of the unemployed among locations is closely related to the distribution of the reference population. For this purpose, we use the concentration index initially proposed by Maurel and Sédillot (1999) to measure industrial concentration, which can be reinterpreted as follows:⁸

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

where:

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

$s_i = \frac{n_i}{N}$ 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 in the country), and $x_i = \frac{p_i}{P}$ being the proportion of reference population settled in that location.⁹ 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.

As opposed to Johnston *et al.* (2003), this index estimates and aggregates 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

⁸ 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.

⁹ 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.

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, giving more relevance to what happens in larger urban areas. If the whole population were only in one location, its value would differ 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.

- ***Measuring concentration with income distribution tools***

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 country, 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 number of unemployed) is shown on the vertical axis. 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). 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.¹⁰

¹⁰ 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).

The Lorenz curve can be decomposed using different population subgroups (in our case, municipal subgroups designed according to their size). 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 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. 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 there are intersections between the Lorenz curves of two distributions, the Lorenz criterion is not conclusive and it is necessary to use complete inequality indices. One of those

indices is the Gini coefficient, which measures the “distance” from the Lorenz curve to the 45 degree line. The expression can be reinterpreted in our case as follows:

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

where $\bar{u}_i = \frac{n_i}{p_i}$ is the unemployment rate of municipality i , and $\bar{U} = \frac{N}{P}$ the national

unemployment rate. The Theil indices are other inequality indicators we adapt to our case. For the sake of simplicity, here we only focus on Theil index with parameters 1 and 2, since the results obtained in the empirical section when using other parameters are analogous. The expressions of these indices in our case are:

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

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

An advantage of Theil 1 is that it can be decomposed by subpopulations, while Theil 2 can do it by factors. In what follows we present these decompositions:

i) **Inequality decomposition by subpopulations** (Shorrocks, 1980). By using this decomposition, we can analyse whether the classification by municipality size is an important dimension in the phenomenon of unemployment concentration. In the case of Theil 1 this decomposition can be expressed as:

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

where $x^{(k)}$ is the population weight represented by subgroup k , $T_1^{(k)}$ the value of the Theil 1 index for that subgroup, and $\bar{u}^{(k)}$ 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 (1982), can be expressed here for T_2 index as follows:¹¹

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

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 \bar{u}_c is the average of such distribution (weighted by municipality size).

4. Comparisons between male and female unemployment

4.1. Data sources

We use an unemployment database which comes from an administrative source: the job-seeker rolls supplied by the public employment service, *Servicio Público de Empleo Estatal* (*SPEE*).¹² In particular, the *SPEE* has information about “unemployed employment seekers” (*DENOs*), which is a wider concept than the one traditionally used for registered

¹¹ In Brülhart and Traeger (2005) this decomposition is used to analyse the concentration of economic activity in Europe per sector.

¹² The *Encuesta de Población Activa*, survey usually used to analyse the labour market in Spain, does not gather any municipal information, so that it cannot be used at this fine geographical scale.

unemployment, since it includes other groups that should be considered as unemployed if the international criteria 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 had access to the *DENOs* data of the Spanish municipalities for January 2005.¹³ These data were 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 population 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 *Instituto Nacional de Estadística* for 2004, as the municipal data for 2005 are not available yet.¹⁴

4.2. Results

As we can see in Figure 1, the male density function of unemployment rates is further to the left and has a more skewed shape, which indicates that for men there is less dispersion across municipalities and a lower average unemployment rate than for women.

¹³ This means that we have the whole set of the unemployed (2,521,595 individuals), but due to confidentiality reasons, we have had no access to enough information about these individuals to allow us an analysis of the causes of unemployment.

¹⁴ 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. Female participation rates in Spain are much lower than male rates (55.7% against 81.1%, according to OECD data for 2003). Therefore, by using the working age group as reference population, instead of the economically active group, our female unemployment rate is much lower than the traditional unemployment rate for women. In the male case, this difference is less acute.

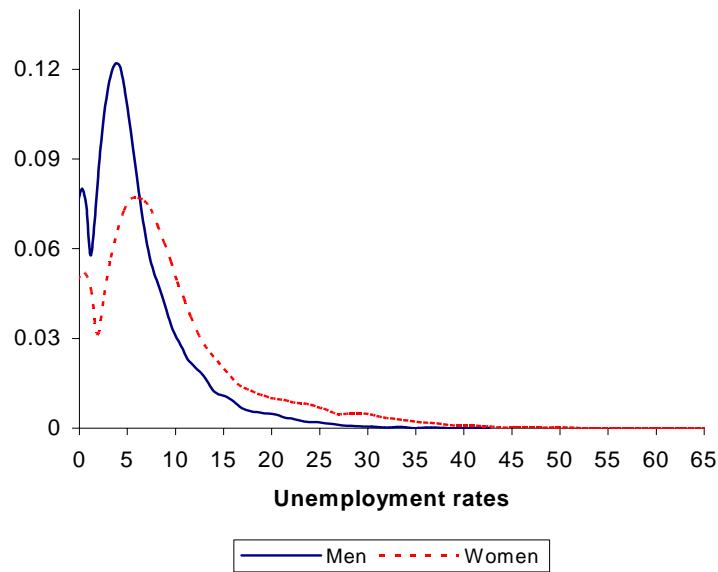


Figure 1. Density functions of municipal unemployment rates

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.¹⁵ The difference between the weighted and the 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.¹⁶

4.2.1. Economic geography measures

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 the proportion of the unemployed, against the total unemployed, living in municipalities included in each interval has to be calculated (see Table 2).

¹⁵ 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).

¹⁶ The standard deviation is 5.1 for women and 2.9 for men (7.8 and 5, respectively, in the unweighted distributions).

| 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 2. 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 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).

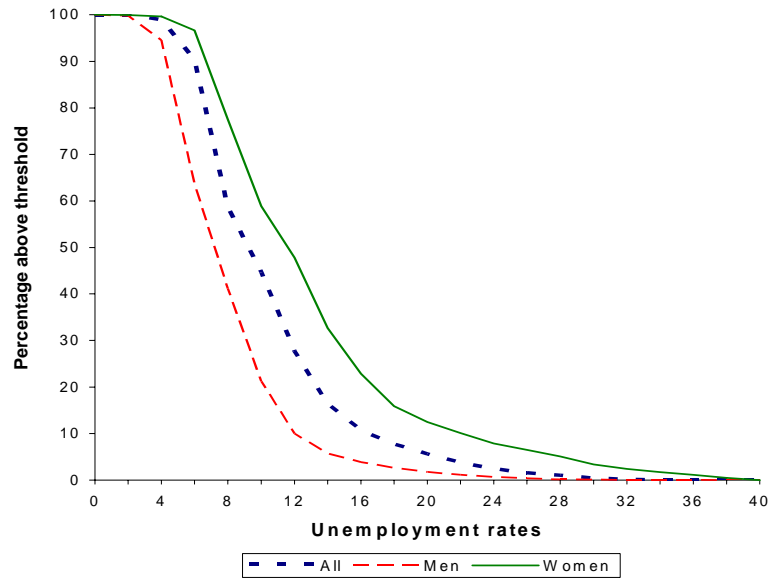


Figure 2. Concentration profile curves

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.

When using the M-S index, 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 3, 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. Since the M-S index value is more negative for women than for men, we could

conclude that female unemployment is relatively less localised in larger municipalities than male unemployment.

| | Women | Men |
|--|--------------|------------|
| Subgroup 1 Less than 2,000 | 0.00024 | 0.00022 |
| Subgroup 2 [2,000, 10,000) | 0.00028 | 0.00023 |
| Subgroup 3 [10,000, 50,000) | 0.00043 | 0.00039 |
| Subgroup 4 [50,000, 100,000) | 0.00398 | 0.00311 |
| Subgroup 5 More than 100,000 | -0.01895 | -0.01206 |
| All | -0.00381 | -0.00153 |

Table 3. Index of spatial concentration (Maurel and Sédillot, 1999)

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) (averages and standard deviations are shown in Table 4). 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 (Table 3). This suggests 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.¹⁷

¹⁷ The fact that the M-S index has higher absolute values as the size of municipalities increases is not surprising, since it is very sensitive to the demographic weight of the units under study.

| | Unemployment rates averages (standard deviation) | | | Number of municipalities ¹⁸ | Working age population (%) |
|--|--|------------------|-------------------|--|----------------------------|
| | All | Men | Women | | |
| Subgroup 1 Less than 2,000 | 8.6 (6.3) | 6.6 (5.2) | 10.8 (8.1) | 6,417 | 9.07 |
| Subgroup 2 [2,000, 10,000) | 9.2 (5.1) | 6.7 (3.7) | 11.8 (6.8) | 1,170 | 17.74 |
| Subgroup 3 [10,000, 50,000) | 8.8 (3.5) | 6.6 (2.5) | 11.1 (4.9) | 400 | 27.05 |
| Subgroup 4 [50,000, 100,000) | 9.2 (3.2) | 7.1 (2.3) | 11.2 (4.3) | 40 | 9.21 |
| Subgroup 5 More than 100,000 | 8.0 (2.4) | 6.6 (1.8) | 9.4 (3.0) | 43 | 36.93 |
| All | 8.6 (3.8) | 6.7 (2.9) | 10.6 (5.1) | 8,070 | 100 |

Table 4. Data summary of unemployment rates by subgroups

4.2.2. Income distribution measures

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.

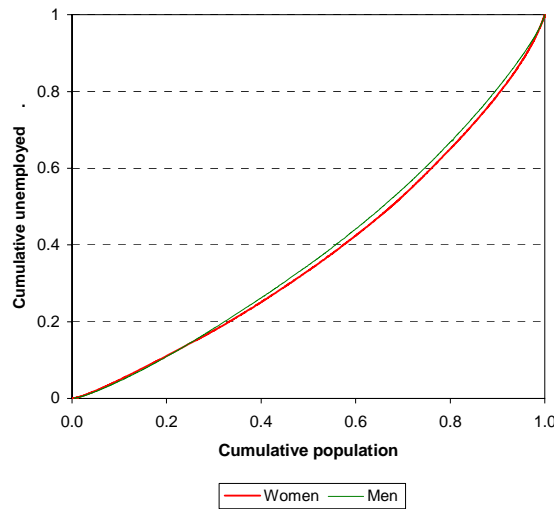


Figure 3. Unemployment Lorenz curves

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 insignificant differences between them).¹⁹ The intersection between both curves does not

¹⁸ Spain has 8,109 municipalities, those with fewer than 10 individuals (in the working age group) have not been considered in the study.

¹⁹ Since we do not work with a sample, but with the whole population of unemployed (2,521,598 individuals), statistical inference is not applied.

allow us to determine which 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 (which allow us to compare any two distributions). When calculating the Gini coefficient and the Theil indices, the levels reached in the case of female unemployment are higher than those attained in the male case (Table 5).²⁰ Thus, 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 5, fifth and first columns, respectively).

| | Unemployed (%) | Gini | Theil 1 | Theil 2 | Theil 2 decomposition by sex (%) | Theil 1 decomposition by municipality size Within – Between (%) |
|--------------|-----------------------|-------------|----------------|----------------|---|--|
| Men | 39.28 | 0.22 | 0.082 | 0.093 | 35.87 | 99.7 - 0.3 |
| Women | 60.72 | 0.24 | 0.099 | 0.116 | 64.13 | 95.9 - 4.1 |

Table 5. Theil indices

The decomposition of 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 5, last column).²¹ 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

²⁰ The analysis has also been undertaken by using Theil -1 and Theil 0, yielding the same results. In order to calculate the Theil 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.

²¹ The results are identical when using Theil 0.

different municipalities subgroups, while for large cities the female unemployment rate is clearly below the level reached in the remaining municipalities (see Table 4).

To further analyse this question, we have decomposed the Lorenz curves by the above subgroups. First, we 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 3, for men and women (see Table 6 and Figures 4A and 4B).

| | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|--|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| MEN | | | | | | | | | | |
| Subgroup 1 Less than 2,000 | 28.51 | 17.63 | 13.13 | 9.61 | 8.26 | 7.77 | 7.26 | 7.05 | 6.71 | 9.50 |
| Subgroup 2 [2,000, 10,000) | 39.42 | 30.12 | 26.26 | 19.11 | 17.00 | 16.56 | 16.17 | 16.06 | 15.71 | 18.21 |
| Subgroup 3 [10,000, 50,000) | 25.84 | 27.18 | 31.95 | 26.35 | 26.18 | 26.91 | 28.16 | 28.23 | 27.91 | 26.99 |
| Subgroup 4 [50,000, 100,000) | 6.24 | 6.43 | 8.10 | 6.79 | 6.82 | 8.07 | 7.39 | 9.69 | 9.82 | 9.66 |
| Subgroup 5 More than 100,000 | 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 Less than 2,000 | 23.60 | 12.80 | 9.38 | 8.40 | 7.37 | 6.91 | 7.18 | 6.47 | 6.33 | 8.77 |
| Subgroup 2 [2,000, 10,000) | 27.33 | 16.23 | 14.41 | 14.89 | 14.81 | 15.82 | 16.98 | 15.58 | 15.73 | 19.41 |
| Subgroup 3 [10,000, 50,000) | 32.09 | 20.74 | 18.32 | 21.62 | 23.26 | 24.61 | 29.42 | 26.00 | 27.90 | 28.17 |
| Subgroup 4 [50,000, 100,000) | 11.39 | 8.57 | 7.46 | 7.88 | 8.45 | 7.71 | 6.61 | 7.98 | 9.84 | 9.93 |
| Subgroup 5 More than 100,000 | 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 6. Contribution of each subgroup, LC_k , to the overall Lorenz ordinate (in %)

Note here that the last column in Table 6 accumulates 100% of the unemployed, and therefore shows the percentage of the unemployed, $s^{(k)}$, that each subgroup of municipalities has on the corresponding groups of men and women. 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 unemployed, both for women and men (Table 6, first column). When considering

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 (Table 6, third column). 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.

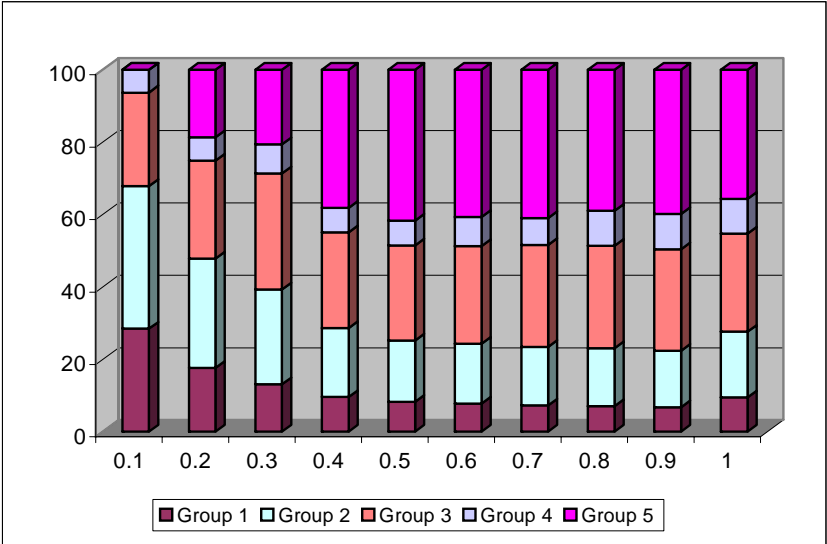


Figure 4A. Contribution of each subgroup to the overall Lorenz ordinate (%): Men

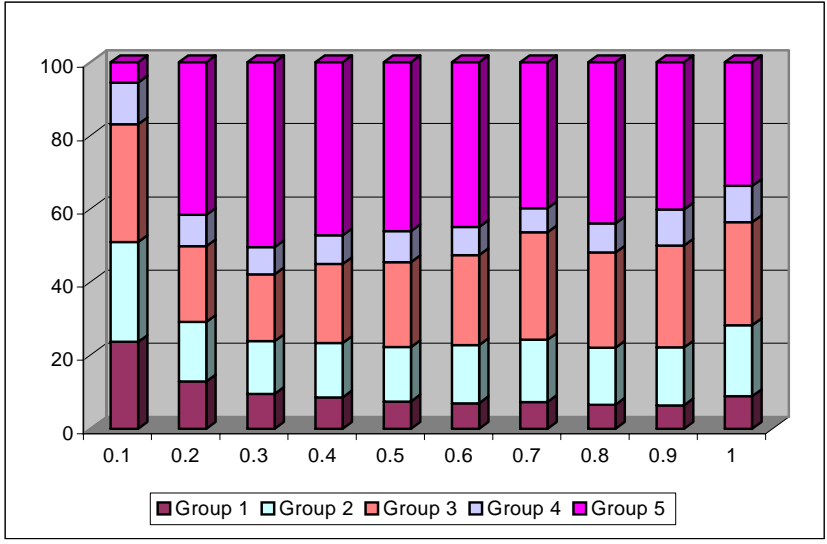


Figure 4B. Contribution of each subgroup to the overall Lorenz ordinate (%): Women

Second, 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 Less than 2,000 | 13.52 | 6.66 | 5.07 | 1.3 | 3.69 | 5.9 | 5.68 | 7.8 | 7.46 | 42.92 | 100 |
| Subgroup 2 [2,000, 10,000) | 9.74 | 8.25 | 8.38 | 1.15 | 4.94 | 7.7 | 8.39 | 10.38 | 10.81 | 30.26 | 100 |
| Subgroup 3 [10,000, 50,000) | 4.29 | 6.7 | 10.66 | 3.94 | 8.11 | 10.31 | 13.02 | 12.85 | 13.7 | 16.42 | 100 |
| Subgroup 4 [50,000, 100,000) | 2.88 | 4.35 | 8.05 | 3.19 | 6.11 | 12.32 | 4.9 | 25.22 | 15.21 | 17.77 | 100 |
| Subgroup 5 More than 100,000 | 0 | 5.7 | 4.85 | 17.5 | 12.64 | 9.68 | 12.53 | 10.11 | 17.32 | 9.67 | 100 |
| Women | | | | | | | | | | | |
| Subgroup 1 Less than 2,000 | 12.96 | 3.27 | 2.76 | 5.04 | 3.98 | 5.38 | 9.89 | 4.74 | 9.11 | 42.87 | 100 |
| Subgroup 2 [2,000, 10,000) | 6.8 | 2.48 | 3.85 | 6.14 | 6.2 | 9.09 | 11.61 | 6 | 11.92 | 35.91 | 100 |
| Subgroup 3 [10,000, 50,000) | 5.49 | 2.67 | 3.35 | 7.75 | 8.27 | 9.54 | 18.03 | 4.94 | 18.3 | 21.66 | 100 |
| Subgroup 4 [50,000, 100,000) | 5.54 | 3.98 | 3.77 | 6.63 | 8.46 | 4.51 | 2.23 | 17.12 | 26.02 | 21.74 | 100 |
| Subgroup 5 More than 100,000 | 0.79 | 12.92 | 12.75 | 8.71 | 10.43 | 10.96 | 5.72 | 22.51 | 9.48 | 5.73 | 100 |

These deciles are determined by the construction of the Lorenz curve of distribution u .

Table 7. Distribution of unemployed in each subgroup by deciles.

Large municipalities is the subgroup with the lowest proportion of male and female unemployed in the top decile, especially for women (9.7% and 5.7%, respectively). Besides, 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. Thus, large municipalities seem to be particular beneficial for women, since these women have more presence in the low tail of the unemployment distribution and lower in the top tail. 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. On the contrary, subgroup 2, which also accumulates a high percentage in the top decile (30% in the male case and 36% in the female), 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).²² In subgroups 3 and 4, the shares of unemployed women in the last ventile (40% and 47.7%, respectively) are significantly higher than those of men (30.1% and 33%, respectively) (Table 7, columns nine and ten). 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.

5. Conclusions

We have shown that unemployed women are more geographically concentrated than men. In particular, the Theil decomposition shows that the contribution of women to the overall unemployment concentration almost doubles that of men. The analysis also suggests that 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 (with respect to the remaining municipalities) indeed makes the size variable an explanatory factor of total female inequality. The different measures used in the analysis point in the same direction (which brings robustness to the results): unemployment is not particularly intense in large cities, but the advantage of living in these cities does not affect women and men equally; agglomeration seems to favour especially the female population.

²² However, the unemployment male rate in subgroup 2 coincides with the national male average (Table 4), as the proportion of unemployed men in the three first deciles of the distribution is larger (Table 7).

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 appears only in municipalities of a certain size, since large and mid-sized cities do not have the same behaviour.

There is little literature on gender gaps in unemployment rates and, as far as we know, nothing has been said yet on how agglomeration can affect these gaps. Explanations of this fact seem rather complex, but it is possible that the mechanisms through which agglomeration affects gender gaps in wages and participation rates can also help to explain the gender gap in unemployment rates. In particular, the matching hypothesis has been shown as more relevant than the learning hypothesis in explaining other urban premiums. Since density facilitates the job matching of individuals of low geographical mobility, urban areas can be especially beneficial for female employment. On the other hand, since women are over-represented in what Petrongolo (2004) calls “atypical” jobs, it is possible that the chances of women of finding a job are higher in larger urban areas.

Another possible source for these spatial differences could be found in the differences in childcare facilities between areas of low and high population density. However, it is not so clear whether this kind of provision affects the unemployment or the participation rate. As evidenced by Azmat *et al.* (2006), domestic responsibilities do not seem to play an important role in the flows from employment to unemployment at a countrywide level, since women with children tend to leave employment for inactivity rather than for unemployment. However, we hypothesize that women with family ties may have less chance of finding a job compatible with their domestic responsibilities in low density areas, where access to childcare services can be more difficult.

Finally, as documented by Azmat *et al.* (2006) and Petrongolo (2004), discrimination against women plays an important role in southern European countries. It would be interesting to explore in future research whether urban and rural areas show differences in this respect. Social attitudes about men being more deserving of employment than women may differ between large cities and small towns, especially in countries such as Spain where women entering the labour market is a quite recent phenomenon.

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