The social cost of unemployment in Spain: Who are the losers?

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Abstract

The social cost of unemployment is an evaluation protocol proposed by Gorjón, de la Rica & Villar (2018) that integrates into a single indicator three different dimensions of this phenomenon: incidence (the conventional unemployment rate), severity (depending on the unemployment duration and the lost income) and hysteresis (the probability of remaining unemployed). This indicator corresponds to the aggregate disutility of unemployed workers and can thus be regarded as a measure of the social welfare loss due to unemployment. We apply here this evaluation protocol to the Spanish labour market, using the official register of unemployed workers compiled by the Public Employment Service, focusing on the differences among the types of unemployed workers that can be defined according to gender, age, level of studies, unemployment duration, and type of compensation received. Then we identify the population subgroups that suffer most the impact of unemployment.

Key words: social cost of unemployment, unemployment duration, incidence, severity and hysteresis of unemployment, Spanish labour market, types of workers.

JEL classification numbers: J64, J65, I31

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1 Introduction

The incidence of unemployment is a very poor indicator of the impact of this problem both for individuals and for society. Trivially, two unemployed individuals of similar characteristics may exhibit rather different welfare levels depending on how long they have been unemployed, whether they receive unemployment benefits, and on the expectations about having a job soon. Similarly, two societies with identical unemployment rates may experience different welfare losses depending on the average duration of unemployment and the nature of the unemployment benefits and social subsidies that is implemented, among other factors. In a recent paper Gorjón, de la Rica & Villar (2018) proposed an indicator that integrates all those aspects by means of a social welfare function that captures the welfare loss to society derived from the disutility of the unemployed. This approach follows closely the standard one in the normative analysis of inequality and poverty. See Chakarvarty (2009), Villar (2017) for a general discussion and detailed references and the contributions by Sengupta (2009), Shorrocks (2009 a, b) and Goerlich & Miñano (2018) for related approaches to the problem.

The evaluation formula they propose is obtained from the aggregation of the individual agents' disutility on being unemployed, which is a function of income loss, unemployment duration and the probability of remaining unemployed. The approach computes the severity of unemployment by taking explicitly into account the (unearned) wages, whether there is access to unemployment benefits or some social subsidies, and the duration of unemployment. Moreover, the impact of unemployment duration on disutility is a convex function, as one additional month of unemployment hurts more the longer the unemployment duration. Indeed, long-term unemployed suffer not only from an accumulation of low income periods but also from the loss of human capital, from a reduction in the probability of exiting their status and from a whole array of personal and social difficulties that affect self-respect, social involvement and social inclusion.[1] The degree of convexity of this function is related to the probability of remaining unemployed (hysteresis).

The social cost of unemployment is obtained by aggregating the disutility of unemployed individuals and results in a function that involves the number of unemployed people, unemployment spells, transition probabilities and income loss (the difference between the market wage and unemployment benefit, if any, for each unemployed worker).

[1] See Winter-Ebmer (2016) and de la Rica and Gorjón (2017) for a discussion. Recall that the United Nations have for many years been using the rate of long-term unemployment as a proxy for (lack of) social inclusion.

In Gorjón, de la Rica & Villar (2018) this evaluation is applied to the Spanish labour market focussing on the differences between the Spanish regions in a given period (January 2015, which corresponds to the closest date to the last wave of data available regarding wages in Spain). We consider here another dimension of this problem: the social cost of unemployment in Spain by different *types* of workers depending on gender, age, level of studies, unemployment duration and type of subsidy perceived. This analysis is important because unemployment has hit very asymmetrically the various types of workers. As an illustration let us point out that young workers are those who have suffered the highest rates of unemployment, but relatively smaller income losses due to lower wages an shorter unemployment duration. Older workers, on the contrary, are those with lower unemployment incidence but longer unemployment spells and higher income losses.

We adopt a twofold approach to the empirical analysis of the social cost of unemployment by types. On the one hand, we compute the social cost separately by categories (gender, age, educational attainment, unemployment duration and compensation). This permits one discussing how men fare with respect to women, or young with respect to old, to put some examples. On the other hand we use a much finer grid computing the social cost for all subgroups resulting from the intersection of those categories (162 subtypes). Here we aim at identifying those population subgroups that suffer most the consequences of unemployment. We find that about 30% of the unemployed bear more than 90% of the total cost and that the most vulnerable groups are long term unemployed over 45 with no unemployment compensation.

The paper is organised as follows. Section 2 describes the evaluation protocol. Section 3 applies this formula to analyse unemployment in Spain for workers with different characteristics, taking as reference the data for the beginning of 2015. Such an estimate shows how this evaluation protocol provides a much better view of the impact of unemployment. A few final comments are given in Section 4 by way of conclusion.

2 The evaluation protocol

2.1 The reference model

Following a conventional utility maximisation programme regarding income and leisure, the *disutility* of an unemployed worker *h* who has been unemployed for a period of q_h months can be expressed as:

$$d_h = c_h(.) f\left(q_h\right) \quad [1]$$

The first term of this product, $c_h(.)$, is a cost function that measures the impact of the average income loss per period, when worker h has been unemployed for q_h periods. This function depends on the lost wage, w_h, and the unemployment benefits or social subsidies received.

Let us suppose that an unemployed worker h receives an unemployment benefit s_h per period, for a maximum of q^* periods, and let z_h denote a social subsidy that he/she would receive otherwise (for the sake of simplicity in exposition we assume that those social subsidies are incompatible with unemployment benefits and indefinite). Then the cost function adopts the following form, when the unemployed worker has the right to unemployment benefits:[2]

$$c_h(.) = \begin{cases} (w_h)^{1/2} - (s_h)^{1/2} & \text{if } \; q_h \leq q^* \\ \dfrac{(w_h)^{1/2} q_h - (s_h)^{1/2} q^* - (z_h)^{1/2}(q_h - q^*)}{q_h} & \text{if } \; q_h > q^* \end{cases}$$

and,

$$c_h(.) = \left(w_h\right)^{1/2} - \left(z_h\right)^{1/2}$$

otherwise (in the understanding that $z_h = 0$ is not excluded).

As for the second term of equation [1], it is assumed that f is a convex function, to give progressively more weight to the average cost with duration, whose degree of convexity is governed by the probability of remaining unemployed according to the following formula:

$$f\left(q_h\right) = \left(q_h\right)^{1+v_h}$$

where v_h is the probability of remaining unemployed for one additional period. This is a function that exhibits a constant elasticity of substitution given by v_h, which consequently varies between a linear and a quadratic function.

Aggregating the disutility of all unemployed workers, with cardinal n^U, and making it relative to the size of the active population, n, we obtain:

$$D_N = \frac{n^U}{n} \times \frac{\sum_{h \in U_N} c_h(.) q_h^{1+v_h}}{n^U} \qquad [2]$$

That is, the social cost of unemployment corresponds to the product of two factors with a clear meaning. The first is simply the *unemployment rate*, which measures the *incidence* of unemployment. The second provides a measure of the

[2] The formula derives from an indirect utility function of the worker that adopts the form $u^* = w^{1/2}$.

severity of unemployment, adjusted for *hysteresis*, and corresponds to the *average disutility* of the unemployed.

By letting r^U denote the unemployment rate and *ADU* the average disutility of the unemployed, equation [2] can be rewritten in a simpler way as follows:

$$D_N = r^U \times ADU \qquad [2']$$

2.2 Heterogeneous agents

Consider now that the population consists of *J* different types of workers, *j* = 1, 2, …, *J* (e.g. age groups). Let n^{Uj} denote the number of unemployed of type *j* in the population, U_{Nj} the set of unemployed of type *j*, and $c_h^j(.)$ the average cost per period of unemployed *h* of type *j*. The social cost of unemployment can then be expressed as:

$$\begin{aligned} D_N &= \frac{n^U}{n} \times \frac{\sum_{h\in U_N} c_h(.) q_h^{1+v_h}}{n^U} \\ &= \sum_{j=1}^{J} \frac{n^{Uj}}{n} \times \frac{\sum_{h\in U_{Nj}} c_h^j(.) q_h^{1+v_h}}{n^{Uj}} \\ &\Rightarrow D_N = \sum_{j=1}^{J} s^{Uj} \times ADU^j \end{aligned} \qquad [3]$$

Where s^{Uj} is *the share* of unemployed of type *j* in the population (*not* the unemployment rate of the type) and ADU^j is the average disutility of the unemployed of type *j*.

This equation permits one analysing the social cost of unemployment by types of workers from different angles. The most immediate is the comparisons of the average disutility of the unemployed,

$$ADU^j = \frac{\sum_{h\in U_{Nj}} c_h^j(.) q_h^{1+v_h}}{n^{Uj}} \qquad [4]$$

which informs us about the impact of unemployment on the welfare of the represantive agent of type *j*. We can assess, for instance, if unemployment is hitting harder a young female unemployed than a mature male unemployed.

It is also interesting to know the proportion of the social cost of unemployment that corresponds to each type of workers, which can be obtained as follows:

$$H_j = \frac{s^{Uj} \times ADU^j}{D_N} \qquad [5]$$

This variable provides a measure of the contribution of each type of unemployed to the aggregate disutility loss and may be a relevant reference when designing policies directed to reduce the impact of unemployment.

3 Implementation: the case of Spain

We now apply this assessment protocol to the Spanish labour market at the beginning of 2015, focusing on the differences between the types of workers that can be defined according to some key demographic features. We use two different databases, one for employed workers (a representative sample of about 170,000 observations) and the other for the unemployed (in this case we use the whole census of unemployed workers, with more than five million observations).

3.1 Data

The reference data are the same as those in Gorjón, de la Rica & Villar (2018) where a more detailed description can be found. The dataset for employed workers is the last wave of the *Spanish Earnings Structure Survey* (SESS 2014), which contains detailed micro-data on the characteristics of employed workers and the various components of their wages. It provides information on the main demographic characteristics (gender, age, educational attainment) as well as information on the key aspects of the labour market (the type of contract, tenure in the firm, occupation and sector of activity, hours worked and detailed information on wages). The range of the hourly wage was set between 2 and 60 euros.[3]

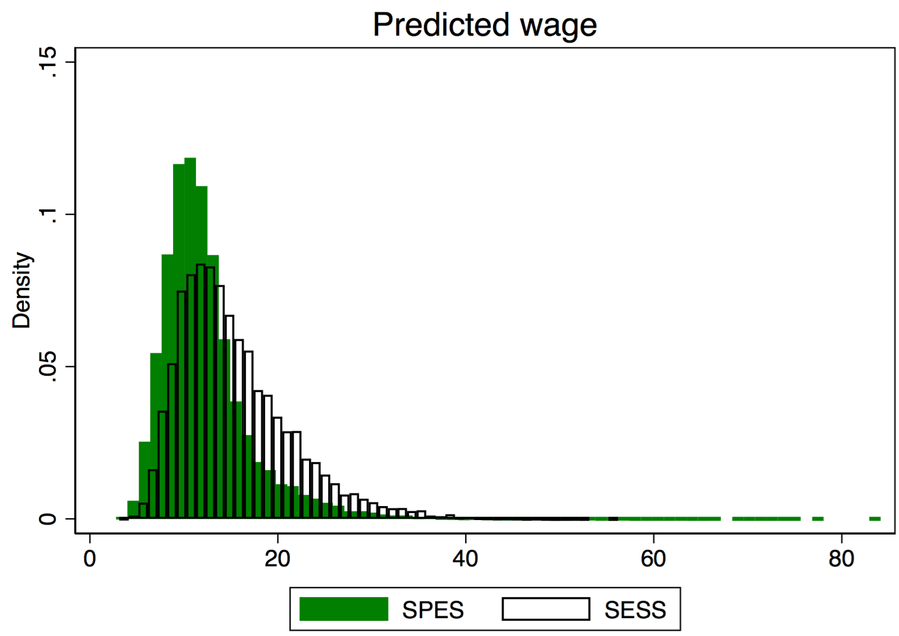
Our second dataset consists of monthly longitudinal information on all individuals registered with the *Spanish Public Employment Service* (SPES) from January 2011 to September 2017. The database includes information on demographic characteristics (gender, age, education level, nationality, postcode and residence, knowledge of other languages), along with labour market information (previous employment experience, occupational and geographical searches, unemployment duration, etc.), and the type of unemployment benefits or social subsidies received. This dataset contains all individuals registered as looking for a job in January 2015 (5,520,253 persons).

[3] Those workers earning less than €2/hour account for 0.76% of the sample and those earning more than €60/hour for 0.91%.

Lost wages are estimated by matching those variables contained in both datasets that are the main determinants for wages: gender (2 groups), age (10 groups), level of education (10 groups), sector of activity (19 groups) and 2-digit sector of occupation (58 groups). We estimate hourly wages and obtain the predicted hourly wage for every worker in the SESS sample. Then we impute that predicted wage to all workers registered as unemployed in January 2015 in the SPES, on the basis of their gender, age, level of education, former sector of activity and former occupation.[4] To be more precise, we create cells from the categories defined by gender, age, education, sector and occupation, and assign an imputed wage for each cell based on the above wage prediction[5]. As a result, two unemployed workers in January 2015 belonging to the same cell would have the same imputed wage.

The distribution of the predicted wages for the 2014 SESS workers and for the unemployed individuals is presented in Figure 1, where the differences in the shapes correspond to the different compositions of the two groups.

Figure 1. Distribution of predicted hourly wages in the 2014 SESS and for the unemployed in the SPES, January 2015.



[4] We drop unemployed individuals with no previous employment experience given that their wages cannot be imputed in the same way and as a group they may have very different characteristics. They account for 0.38% of unemployed individuals. We also drop those unemployed individuals who only seek part-time work, as their disutility function might be different. They account for 0.94%.

[5] Following the recommendation of López-Laborda, Marín-González and Onrubia (2017), we use a Generalized Linear Model to estimate the predicted wage in order to avoid bias in the estimation results due to the retransformation problem from logarithms to wage levels.

In line with to the imputed hourly wage, we estimate the monthly wage as 22 (days/month) x 8 (hours/day) x hourly wage (€/hour). From the monthly individual information on types of unemployment benefit and unemployment duration, we impute the amount of unemployment benefit that each unemployed individual is receiving and compute the average cost of unemployment for each unemployed worker. More precisely, the monthly unemployment benefit is calculated as 70% of the monthly wage for the first 180 days and 50% of the monthly wage for the following months in which it is received. It is upper and lower bounded at €1411.83 and €501.98, respectively. The amount corresponding to social subsidies is 75%, 80% or 107% of the Multiple Effects Public Income Indicator (set at €532,51)[6] depending on the type.

Next we estimate the probability of individuals finding a job in the next month (a discrete choice model where the dependent variable takes a value of 1 if individuals find work in the next month and zero if they remain unemployed). Then we consider three different groups of unemployed workers: (1) those who receive unemployment benefits (UB); (2) those who receive social subsidies (SS); and (3) those who receive no income (N).

The disutility of an unemployed worker *h* who receives unemployment benefits is obtained by directly applying the corresponding formula, $\left(w_h - s_h\right)q_h^{1+v_h}$. The richness of the dataset enables the monthly disutility to be computed for each unemployed individual since their entry into unemployment, according to the type of unemployment benefit that they are receiving.

Among the group of unemployed workers who have received social subsidies at any time, three different situations can be found: (a) unemployed workers who have exhausted their unemployment benefits and then receive a social subsidy; (b) unemployed workers who have been receiving a social subsidy throughout their period of unemployment; and (c) unemployed workers who started receiving social subsidies after a period of not receiving any benefit in 2015.

Similarly, those receiving no payments fall into four types: those who have exhausted unemployment benefits, those who have received social subsidies for a period and ceased to receive them, those who received unemployment benefit, then social subsidies but have exhausted both and those who have never received any payments.

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[6] The upper and lower bounds and the social subsidies depend on the Multiple Effects Public Income Indicator, which has remained unchanged at €532.51since 2011.

3.2 Empirical Results: The Social Costs of Unemployment in Spain for different types of workers

Now we present the main results on the Spanish labour market, using the 2014 data on wages (last available wave from the *Spanish Earnings Structure Survey*) and those of January 2015 for the Spanish Register of Unemployed Workers. The empirical analysis refers to a single period and focuses on comparing (per capita) social costs of different types of unemployed workers that are described in Table 1.

Table 1: Categories and types of unemployed workers

Categories	Types
Gender	Female
	Male
Age	Less than 25 years
	Between 25 and 45 years
	More than 45 years
Education	Low
	Medium
	High
Unemployment duration	Less than 1 year
	Between 1 and 2 years
	More than 2years
Compensation	Unemployment benefits (UB)
	Social Subsidies (SS)
	None

The key data are gathered in Table 2. The first two columns of this table provide the values of the unemployed population shares (i.e. the distribution of total unemployed by types within each category) and the unemployment shares (the ratio between the unemployed of each type and the overall active population). The next three refer to duration (in months), average cost per period, and probability of remaining unemployed, for the population subgroups considered. Those data already show some salient features of those types of unemployed workers, which can be summarised as follows:

(i) The overall unemployment rate in Spain is more than twice the average of the OECD countries.

(ii) The average probability of remaining unemployed is extremely high (0.957 for the whole population of unemployed, with values above 0.9 for all types of unemployed). There is a small variance among the types.

(iii) The average unemployment duration is also very high (about 19 months) with extreme values for those unemployed for more than two years (more than 42 moths), which represent almost one third of all unemployed.

(iv) Unemployment duration varies substantially between the different types of unemployed. Women's duration is about 14% higher than that of men. Much larger are the differences by age (older unemployed average duration exceeds 2.5 times that of the younger). Differences by level of studies are relatively small. Those without unemployment benefits also exhibit substantially higher duration.

(v) The data regarding average cost per month exhibit the expected pattern and reflect the differences in wages and unemployment benefits. Women cost is higher than that of men, in spite of smaller wages, due to smaller unemployment compensations. There are small differences by age due to the balancing effect of wages and unemployment benefits. The cost of those unemployed with higher education is much larger than those with lower educational achievements. The cost of those unemployed receiving no compensation (almost 60% of the total) is about 2.5 times those with unemployment benefits and a some 1.5 times those with social subsidies.

Table 2: Unemployment shares, duration, average costs, and probability of remaining unemployed by types (Spain, 2015)

		Unemployed Population Shares	Unemployed over active population s^{UJ}	Duration q	Average cost $c(.)$	Prob. v
Total		100.0%	18.17%	18.83	35.32	0.96
Gender	Female	50.7%	9.21%	20.22	35.94	0.97
	Male	49.3%	8.96%	17.41	34.59	0.96
Age	< 25	6.1%	1.10%	9.53	32.61	0.96
	25 - 45	48.5%	8.80%	14.96	34.40	0.95
	> 45	45.5%	8.27%	24.20	36.07	0.98
Education	Low	45.6%	8.28%	18.80	32.35	0.97
	Medium	39.2%	7.13%	19.37	35.65	0.96
	High	15.2%	2.76%	17.53	43.97	0.95
Duration	< 1 year	49.8%	9.04%	4.27	30.91	0.95
	1-2 years	18.4%	3.34%	16.96	31.31	0.98
	> 2years	31.8%	5.78%	42.68	36.94	0.99
Benefits	UB	17.2%	3.12%	7.69	16.47	0.94
	SS	23.8%	4.32%	21.39	27.54	0.97
	None	59.0%	10.72%	21.04	40.52	0.97

Table 3 summarizes the main results in terms of the social cost of unemployment. The first column shows the data regarding the average disutility of the unemployed depending on the type (equation [4] above). The figures underline the fact that women, older unemployed, unemployed for more than two years and those without any benefit are those suffering most. The second column, which obtains from equation [5], describes the extremely asymmetric distribution of the social cost by types within each category. Unemployed women account for 60% of the total cost, when considering workers divided by gender. This is due to women's longer unemployment spells and larger costs, as unemployment rates are similar. When divided by age, we observe that those unemployed over 45 account for almost 70% of the total cost. This group exhibits a larger share of total unemployed, a much larger duration and greater costs. The young, on the contrary, represent a small share of total unemployed, with much shorter duration and lower costs, which translates into a negligible share of the total cost. Those with low or medium education bear some 84% of the total cost when divided by educational attainment, Here there is some balancing effect, as those with higher education have higher costs but a much smaller share of the unemployed (with similar values in terms of duration).

Table 3: Social cost of unemployment by types (Spain, 2015)

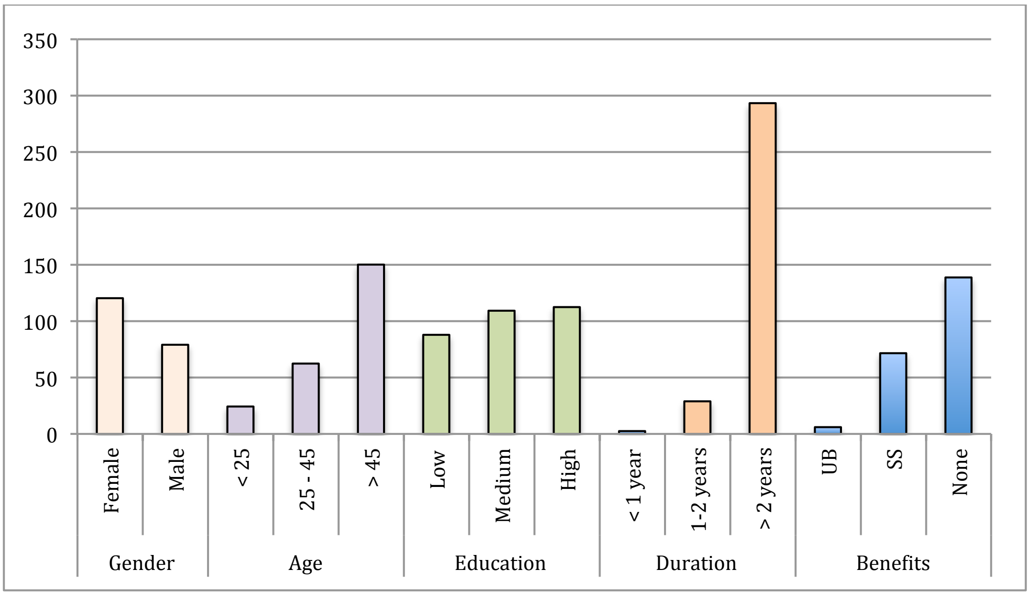
		ADU^j	H_j	Cost share minus unemployment share
Total		30417	-	
Gender	Female	36609	61%	10.3
	Male	24051	39%	-10.3
Age	< 25	7405	1%	-5.1
	25 - 45	18967	30%	-18.5
	> 45	45677	68%	22.5
Education	Low	26731	40%	-5.6
	Medium	33232	43%	3.8
	High	34216	17%	1.8
Duration	< 1 year	766	1%	-48.8
	1-2 years	8795	5%	-13.4
	> 2 years	89256	93%	61.2
Benefits	UB	1835	1%	-16.2
	SS	21790	17%	-6.8
	None	42215	82%	23.0

Those unemployed more than two years account for more than 90% of all unemployed. Here duration is the leading factor that explains such a distribution. Finally, when classified according to compensation, those without any benefit bear more than 80% of the total cost. In this case it is mostly the effect of the share of unemployed and the duration what explains that figure. Needless to say duration and unemployment benefits are closely related.

The third column shows the difference between the distribution of social cost and unemployment within each category. Those data illustrate well that focusing on unemployment shares provides a distorted image of the impact of unemployment in society.

Figure 2 provides a graphical illustration of the differences in the average disutility of the unemployed by type in relative terms (i.e. letting Spain's average disutility of the unemployed equal to 100). The different disutility between unemployed women and men is mostly due to the larger duration of women's unemployment, as the average cost is similar. Average disutility of unemployment is increasing with age, mostly due to the impact of duration. Disutility also increases with the level of studies even though in this case the leading factor is the average cost. The average disutility of those unemployed for more than two years is more than 100 times that of those unemployed for less than a year. In this case duration is the key element that explains such a huge difference (duration of those unemployed for more than two years is more than 10 times that of those unemployed for less than a year). With much smaller impact, average cost and probability of unemployment also contribute negatively for those with longer unemployment spells. The average disutility of those unemployed receiving no compensation is 23 times that of those with unemployment benefits and twice that of unemployed with social subsidies. In this case both duration and average cost contribute similarly to those differences.

Figure 2: Relative disutility of the unemployed by type (Spain 2015)



We now complement those data on the social cost of unemployment by showing how those costs are distributed within the types, by comparing their cumulative distributions. Figure 3 describes the distribution function of the cost for the unemployed workers by different demographic characteristics. Figure 3.A corresponds to all unemployed workers together. The mean value is about ten times the median, which tells us that the distribution is strongly skewed.

Figure 3.B shows that the distribution of the social cost of unemployment between men and woman is similar, with the distribution of men stochastically dominating that of women. That means that men fare better than woman at all levels of cost.

Age groups present a very unbalanced distribution. The group of unemployed older than 45 is the one that suffers most, due to longer unemployment spells and larger income losses. This applies not only to average values but also to all levels of the distribution. Figure 3.C provides a clear illustration of the sharp stochastic dominances of the younger.

The data concerning the social cost of unemployment by educational levels show the cost moves monotonically with the level of education. The same pattern appears regarding income losses and the opposite pattern for duration (which varies very little between groups) and probability of remaining unemployed. The distribution of the costs is very similar in all three groups, as shown in Figure 3.D.

The data on duration makes it clear that the key problem is that of very long term unemployed (more than two years), with a per capita cost about ten times that of the next group. The average duration of those unemployed for more than two years is close to four years with a substantially higher income loss and a probability of remaining unemployed close to 1. The other groups of unemployed represent a much smaller problem. Figure 3.E describes the corresponding cumulative distributions that are self-explanatory.

The results regarding the type of compensation received are those that one would expect. Those unemployed with no compensation exhibit a a per capita cost more than twenty times that of those who get unemployment benefits. The income loss is larger the smaller the compensation, as it should be, but the data on average duration and probability of remaining unemployed are slightly higher for those receiving social subsidies than for those receiving nothing. The cumulative distributions in Figure 3.G show that the group getting social subsidies and the group with unemployment benefits are very similar and stochastically dominate those with no compensation.

Figure 3. Cumulative distribution of the social cost of unemployment. Different demographic groups (Spain 2015)

Figure 3.A. All unemployed

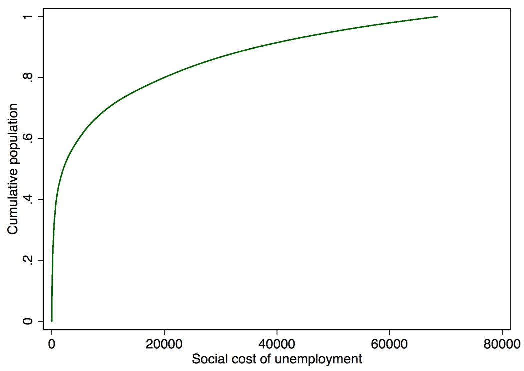


Figure 3.B. By gender

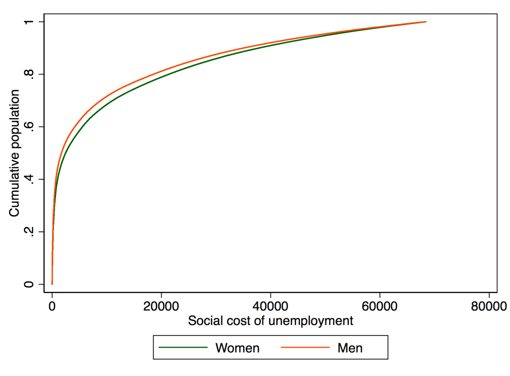


Figure 3.C. By age

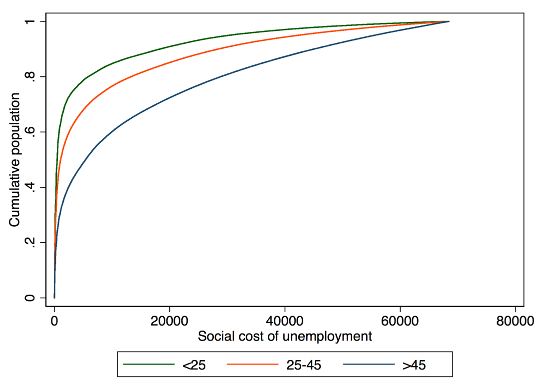


Figure 3D. By education level

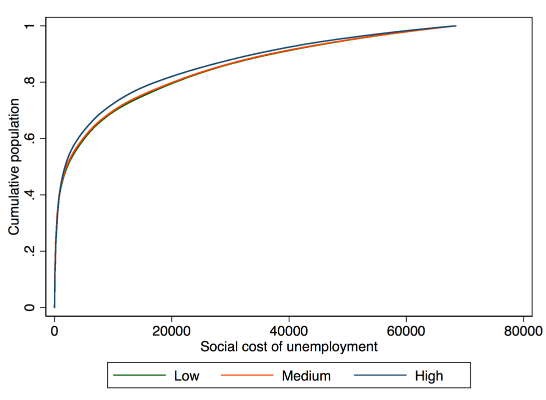


Figure 3.E. By unemployment duration

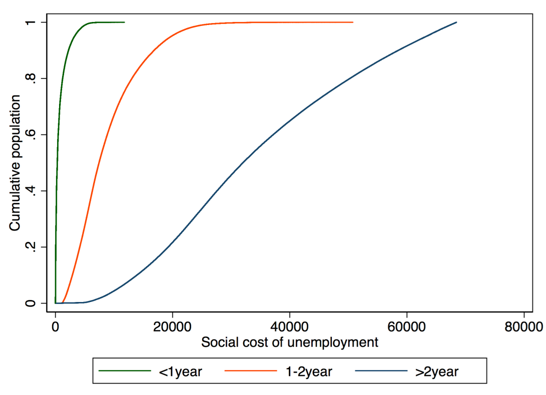
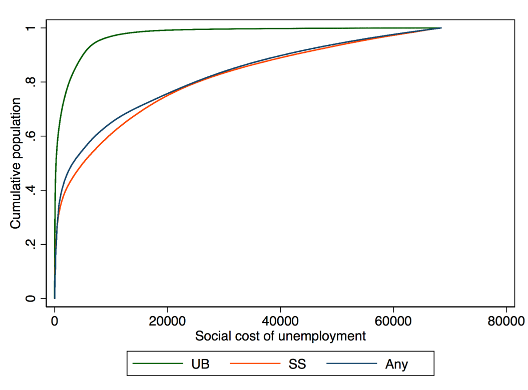


Figure 3F. By unemployment benefit



3.3 Identifying the worst-off population subgroups

We now consider the social cost of unemployment using a much finer grid of types with the goal of identifying those groups of workers that suffer more due to unemployment. To do so we first consider the cells that derive from the intersection of all the types discussed above, which results in a total of 162 subtypes (the result of multiplying all those types, $2\times3\times3\times3\times3=162$). An example of a subtype would be that of young women with tertiary education that are unemployed for more that one year but less than two and receive social subsidies. As one would expect, some of those subgroups are extremely thin (for instance the subgroup just mentioned consists of 12 people out of five million unemployed). This suggests that it would be wise defining a criterion to reduce the number of cells in order to focus on those subgroups that are more relevant from a social welfare viewpoint. To do so, we calculate all the relevant data for those 162 subgroups and then establish a cut-off in terms of the share of the aggregate social cost.

In order to identify the less favoured subtypes we define a *relevant population subgroup* of unemployed as one that represents at least the 0.5% of the aggregate social cost of unemployment. In this way we make a selection combining the size of the cell (how many unemployed are involved) and the size of the per capita cost. The key data are presented in Table 4.

Table 4: Relevant subgroups of unemployed

Type (cells)					% total cost	% total unemployed
Gender	Age	Education	Duration	Compensation		
Woman	> 45	Med	> 2	None	15.74%	2.87%
Woman	> 45	Low	> 2	None	13.15%	3.09%
Man	> 45	Low	> 2	None	7.49%	2.58%
Woman	25-45	Med	> 2	None	7.31%	2.50%
Man	> 45	Med	> 2	None	6.63%	1.75%
Woman	> 45	High	> 2	None	5.27%	0.79%
Man	> 45	Low	> 2	SS	4.74%	2.88%
Woman	25-45	High	> 2	None	4.61%	1.49%
Man	25-45	Med	> 2	None	4.08%	1.59%
Woman	25-45	Low	> 2	None	4.07%	1.76%
Man	25-45	Low	> 2	None	3.71%	1.74%
Woman	> 45	Low	> 2	SS	2.97%	1.62%
Man	> 45	Med	1-2	SS	2.84%	1.55%
Woman	> 45	Med	> 2	SS	2.57%	1.37%
Man	> 45	High	> 2	None	2.47%	0.49%

Man	25-45	High	> 2	None	1.92%	0.58%
Man	> 45	High	> 2	SS	0.64%	0.28%
Woman	> 45	High	> 2	SS	0.50%	0.25%
	Total				90.72%	29.19%

The key points of this selection are evident:

(i) The set of relevant subtypes consists of just 18 out of 162 cells, which represent the 29% of total unemployed and account for 91% of the total cost.

(ii) All but one of those subgroups consists of workers unemployed for more than two years.

(iii) None of the subtypes that receives unemployment benefits appears as a relevant subgroup.

(iv) Twelve out of the eighteen selected subgroups are made of unemployed aged over 45, with no group of young unemployed present.

(v) The 18 subgroups are evenly distributed by gender and by level of education, even though women and those with lower education are among those with larger shares of social cost.

(vi) The first five subgroups account for more that 50% of the total cost and some 13% of the total unemployed.

Those data point out clearly that those suffering more the consequences of unemployment are long term unemployed, aged 45 or more, with no unemployment benefits, with worst outcomes in general for women and low educated workers.

4 Final remarks

We have presented here a protocol to evaluate the social cost of unemployment that integrates three different dimensions: incidence (the unemployment rate), severity (that computes duration income losses) and hysteresis (the probability of remaining unemployed. The synthetic formula corresponds to the average disutility of the unemployed.

Armed with this formula we have analysed the situation of the Spanish labour market in 2015 considering different criteria to classify the workers (gender, age, educational attainment, unemployment duration and unemployment compensations). We have first study the results for each of those categories separately, finding that women fare worse than men (mostly due to duration), that the social cost grows with age, that differences by levels of studies are not very large (compensation effects of income losses and duration), and that the social cost of those unemployed for more than two years and those with no unemployment compensation are extremely high.

We have also analysed the situation of those subgroups that derive from the intersection of all those categories, in order to identify those population subgroups that are worst off (the losers, so to speak). 18 out of the 162 population subgroups account for more than 90% of the total cost of unemployment and represent about 30% of the total unemployed. The most vulnerable groups are those corresponding to long term unemployed over 45 and without any compensation. Neither educational attainment nor gender appear as the key variables to identify those who are worst off (even though women and those with lower attainment are worse). The leading factors that explain the higher social cost are related to age (over 45), duration (more than two years) and compensation (no compensation). The results presented in Table 4 permit one identifying those population subgroups more in need and hence those to be targeted by any sensible public policy. It appears, in particular, that the high unemployment rates suffered by the young have relatively small costs due to the effect of the low income losses and short spells.

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