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On the three i's of employment and the Spanish labour market*

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ABSTRACT

We present an evaluation model that aims at developing a comprehensive index of employment. This index involves what, by analogy, we call the three i's of employment: *Incidence* (the employment rate), *Intensity* (the average number of months actually worked by the employed), and *Inequality* (a measure of dispersion in the distribution of employment lengths). We apply our methodology to Spanish data, comparing the situation between 2013 and 2017, both for types of workers and for regions. We find that incidence and intensity move in the same direction, increase with age within each level of educational attainment, both for males and females, and with the average level of educational attainment. These outcomes indicate that, in spite of high levels of growth and employment creation, the incidence of employment has not improved very much (2.7% for males and 1.2% for females), while the increase in the employment lengths of employed workers has been even smaller (the increase of men being three times that of women). The combined effect of the three factors, incidence, intensity and inequality, yields more encouraging results but also shows large differences between men and women (6.6% vs. 2.7%). Finally, we also find that those Spanish regions that are below the mean in terms of employment (Andalusia, Castilla la Mancha, Valencia and Murcia) are further below in terms of the joint evaluation.

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1 Introduction

The labour market is experiencing an array of changes that requires re-thinking the way in which we measure its main indicators. These changes have appeared partly as a consequence of the economic crisis and partly as a consequence of a more profound shift in the way labour tasks and the relationships between firms and workers are organised. Technological change and globalisation are recognised as the driving forces of these long-run transformations (e.g. OECD 2017). There are two consequences of these changes we would like to underline here. First, the extension of self-employment, part-time jobs and temporary contracts that seems to go hand-in-hand with the decline of the traditional model of employment; second, the asymmetrical impact of those changes on different types of workers and geographical areas. Such dynamics entail that the conventional notions of employment and unemployment rates, the key variables hitherto used to assess labour market performance, become less and less informative (see the discussion in the ILO report 2019).

An implication of the aforementioned changes, insofar as occupation is concerned, is that attention must be paid not only to the differences in employment and unemployment levels, but also to duration: unemployment spells and employment lengths also provide relevant information for understanding labour market performance. The data show that declining unemployment rates can be found accompanying an increase in the average length of unemployment spells. Similarly, the number of months per year worked by those in employment varies substantially across time, regions and types of workers. Put in other words, the data strongly suggest that both the *incidence* and *intensity* of employment and unemployment need to be considered, as they may exhibit different patterns depending on the types of workers in question.

Needless to say, these are not the only aspects that deserve consideration, because evaluating the labour market also involves addressing the effect of changes in real wages, unemployment benefits, the quality of jobs, etc. Here however we shall focus just on the impact of duration in the assessment of the labour market as a first step towards a more thorough evaluation by means of synthetic indicators.

Borrowing some ideas from the literature on inequality and poverty, we aim at developing a comprehensive index of employment that takes into account three different aspects: *Incidence* (the employment rate), *Intensity* (the average number of months actually worked by the employed) and *Inequality* (a measure of dispersion in the distribution of employment lengths). These are the three i's of employment. The incidence and intensity of employment are purely descriptive measures of the labour market that can easily be combined into a single indicator. Taking stock of inequality on the other hand involves introducing normative considerations into the analysis that have to be dealt with explicitly. Fortunately, there is a well-established literature on the measurement of inequality and poverty from a normative point of view that helps us in this endeavour (see, for instance, Charavarty, 2009 or Villar, 2017).

Some of these ideas have already been applied to the analysis of the labour market, especially regarding the measurement of unemployment. The desire to obtain better measures of the labour market has induced the US Bureau of Labour Statistics (BLS) to design six alternative unemployment indicators, from U1 to U6, that derive from using different levels of comprehensiveness in the definition of the unemployed. Computing duration in an index of unemployment already appears in the works of Sengupta (2009) and Shorrocks (2009a, b), which involve transposing some conventional poverty measures to this context. See also Goerlich & Miñano (2018). Another contribution along these lines is that of Gorjón, de la Rica & Villar (2018, 2019), who provide a measure of the social cost of unemployment obtained by aggregating the disutility of the unemployed. Such a measure involves three different aspects of unemployment: incidence (the conventional unemployment rate), severity (which takes into account both duration and income losses), and hysteresis (the probability of remaining unemployed for one additional month). It is also worth mentioning the works of Herrero, Soler & Villar (2018) and Herrero & Villar (2019), who provide an assessment of the labour market by comparing distributions of workers between different types of employment (permanent and temporary) and unemployment (short and long term).

The present contribution differs from those mentioned above in the following respects: first, we focus on employment, rather than unemployment, which entails treating duration differently (months worked per year rather than total months of unemployment); second, we build a social evaluation function in the spirit of the welfare evaluation of income distributions (an average value deflated by a conventional inequality index), rather than an index obtained from poverty measures; third, we aim to measure the impact of duration on the evaluation of employment, leaving aside the effect of wages, unemployment benefits or social subsidies.[1] By contrast to Herrero, Soler & Villar (2018) and Herrero & Villar (2019), we provide an evaluation in which

[1] Here we adopt a similar strategy to that of Dasgupta (2009) and Shorrocks (2009a, b), who also base their analysis on the impact of duration when measuring unemployment.

employment is recorded in terms of duration, rather than the type of contract signed.

The paper is organised as follows. Section 2 presents the evaluation model that results in an indicator made of three different terms: the employment rate, which provides the incidence; the average number of months worked in a given year by those who are employed, which captures the intensity of employment; and inequality, which refers to the dispersion of the employment lengths among the whole active population. Note that even though the focus is on employment, the unemployed are part of the social evaluation since they enter indirectly in the employment rate and directly in the inequality measure.

Section 3 provides an application to the Spanish labour market, focusing on the changes between 2013, the worst year of the economic crisis, and 2017. Even though this is a mostly descriptive analysis, it illustrates that the measurement protocol we propose here illuminates some features of the labour market that may otherwise remain hidden, features that are relevant for the design of policies. The empirical analysis focuses on the differences between types of workers (classified by gender, age and educational attainment) and the Spanish regions.

2 The model

Let us start by focussing on the welfare evaluation of the employed regarding a given year, a given society, and a single category of workers, so that we can skip many subscripts at this early stage. Let $N = \{1, 2, \ldots, n\}$ stand for the active population of the society under consideration, in the chosen year, and let E_N denote the set of employed workers in N, with cardinal n^E. We denote by s_h the *work length*, given by the total number of months that agent h has worked during the year. Vector $\mathbf{s} = (s_1, s_2, \ldots, s_n)$ describes the distribution of the total number of months worked and includes those workers who have been unemployed for the whole period (which will appear with values $s_h = 0$).

The average length of work in that year is simply given by:

$$\mu(\mathbf{s}) = \frac{1}{n} \times \sum_{h \in E} s_h \qquad [1]$$

Equation [1] can be rewritten in a more intuitive way as:

$$\mu(\mathbf{s}) = \frac{n^E}{n} \times \frac{1}{n^E} \sum_{h \in E} s_h = e_N \times \mu^E(\mathbf{s}) \qquad [1']$$

That is, the average length of employment corresponds to the product of the employment rate, e_N, and the average length of employment among the employed workers, $\mu^E(\mathbf{s})$. In other words, the *incidence* times the *intensity*.

This is a purely descriptive measure that introduces the intensity of the employment as a relevant aspect in the measurement. We would like next to evaluate the vector of employment lengths, **s**, from a social welfare perspective, by introducing distributional considerations. We follow here the conventional approach in inequality measurement.

Let $W:\mathbb{R}^n_+ \to \mathbb{R}$ stand for our welfare evaluation function, which we assume to be continuous. We can introduce the value judgements for the evaluation as restrictions on the functional form of this mapping. Let us present the standard value judgements and its implications.

- ***Symmetry:*** Let $\pi(\mathbf{s})$ denote a permutation of vector **s**. Then, $W(\mathbf{s}) = W(\pi(\mathbf{s}))$.
- ***Strict quasi-concavity:*** $\forall\, \mathbf{s}, \mathbf{s}' \in \mathbb{R}^n_+, \forall\, \lambda \in (0,1)$ we have:

$$W\left(\lambda \mathbf{s} + (1-\lambda)\mathbf{s}'\right) > \min\left\{W(\mathbf{s}),\ W(\mathbf{s}')\right\}$$

- ***Homogeneity of degree one***: $\forall\, \mathbf{s} \in \mathbb{R}^n_+, \forall\, \lambda > 0, W(\lambda \mathbf{s}) = \lambda W(\mathbf{s})$.
- ***Scale***: $W(k, k, \ldots, k) = k$.

The first two properties introduce the key value judgements. *Symmetry* establishes that permuting the entries of vector **s** does not change the evaluation. That is, everybody enters the evaluation on an equal foot (a property sometimes expressed as "names do not matter"). *Strict quasi-concavity* expresses the idea that reducing inequality enhances welfare. That is, working two people for six months each is better than one working for twelve and the other remaining unemployed the whole year. Clearly these two properties are more compelling the more homogeneous are the workers in the society under consideration.

The other two properties are mostly operational. *Homogeneity* says that if we multiply all employment lengths by a given constant, then the associated welfare is multiplied by this constant (it can be regarded as the counterpart of scale independence in inequality indices). Note that this property implies monotonicity along rays. *Scale* is an assumption that defines the units in which we are going to measure welfare. It establishes that when all lengths are equal, we can take the average length as the welfare value of distribution, which amounts to adopt a *time metric* for welfare analysis.

We now define the *egalitarian equivalent employment length*, $\xi(\mathbf{s}) \in \mathbb{R}_+$, as the number of months such that:

$$W(\mathbf{s}) = W\left(\underbrace{\xi(\mathbf{s}), \xi(\mathbf{s}), \ldots, \xi(\mathbf{s})}_{n\ times}\right) \qquad [2]$$

That is, $\xi(\mathbf{s})$ is the number of months that if worked by all agents would produce a welfare level equal to the actual one. Note that the welfare is defined over the whole active population and not only on the employed workers.

The continuity of W and the property of homogeneity ensure that equation [2] is well defined. That is, for all $\mathbf{s} \in \mathbb{R}^n_+$ there exists a unique scalar, $\xi(\mathbf{s}) \in \mathbb{R}_+$, that satisfies that equation. Moreover, strict quasi-concavity ensures that $\xi(\mathbf{s}) \leq \mu(\mathbf{s})$, with equality holding if and only if $s_h = \xi(\mathbf{s}) \ \forall h$. Hence, following the framework developed by Atkinson (1970) and Sen (1973), we can use the difference between those two values as a measure of inequality as follows:

$$I(\mathbf{s}) = 1 - \frac{\xi(\mathbf{s})}{\mu(\mathbf{s})} \qquad [3]$$

This is actually a family of inequality indices that is implicitly defined by the form of the egalitarian equivalent term, which in turn depends on the particular social evaluation function adopted in [2]. Hence each inequality index defines a specific social welfare function and vice-versa (the properties above ensure a one to one correspondence; see Blackorby & Donaldson 1978).

Applying now the property of scale to equation [2], we conclude that:

$$W(\mathbf{s}) = \xi(\mathbf{s}) \qquad [4]$$

Combining equations [3] and [4] we obtain:

$$W(\mathbf{s}) = \mu(\mathbf{s})\left[1 - I(\mathbf{s})\right] \qquad [5]$$

Or, put in a slightly different way,

$$W(\mathbf{s}) = e_N \times \mu^E(\mathbf{s}) \times \left[1 - I(\mathbf{s})\right] \qquad [5']$$

That is, the welfare evaluation of the distribution of employment lengths is the product of three terms, which correspond to the well-known three *i*'s of incidence, intensity and inequality.

Equation [5'] is a simple and very intuitive expression. Note that for each inequality index this equation defines a welfare function that permits one evaluate employment lengths distributions. Also observe that the inequality measure refers to the inequality in the distribution of lengths in the whole active population whereas the intensity refers to the average length of the employed workers. This feature imposes some restrictions on the inequality indices that can be used, due to the presence of zeroes in that vector. Fortunately the Gini index, perhaps the most popular and widely used inequality index, is compatible with the presence of zero values and will be the one we choose for our evaluation. That is to say, the specific social welfare function we propose here is the following:

$$W(\mathbf{s}) = e_N \times \mu^E(\mathbf{s}) \times \left[1 - G(\mathbf{s})\right] \qquad [6]$$

where $G(\mathbf{s})$ is the Gini index of distribution **s**.

Note that, as $e_N \times \mu^E(\mathbf{s}) = \mu(\mathbf{s})$, equation [6] is simply the average duration of employment adjusted by inequality according to the Gini index. Yet keeping the formulation in [6] is useful in order to keep track of the different elements involved.

Remark: *From now on when we speak of "employment welfare" or simply of "welfare", we refer to the result of measuring employment according to equation [6].*

3 The Spanish labour market in 2013 and 2017

We now apply this evaluation protocol to the Spanish labour market by comparing two different years, 2013 and 2017. 2013 was the worst year of the economic crisis that started in 2007, while 2017 is the last year for which the required data are available. Analysing the change during this period can be regarded as an assessment of the recovery of employment in Spain. Most of the discussion refers to the analysis of the differences between types of workers, but we shall also consider the differences between the average values of Spanish regions.

As far as the types of workers are concerned, we divide the active population into 40 different types, according to the following criteria:

(i) *Gender* (2 groups): Men and women

(ii) *Level of educational attainment* (4 groups): Primary (P), which corresponds to ISCED 0 and 1; Compulsory (C), which corresponds to ISCED 2; Secondary (S), which corresponds to ISCED 3 and 4; and Tertiary (T), which corresponds to ISCED 5 and 6.

(iii) *Age* (5 groups): 16-25 (1), 26-35 (2), 36-45 (3), 46-55 (4), and 56-65 (5).

Those groups yield the 40 types mentioned (2 x 4 x 5). The figures below will be presented in terms of men and women, and using the following codes for the types: from P1, P2, ..., P5 for those with primary education and different ages, from the youngest to the eldest, to T1, T2, …, T5, for those with tertiary education and age groups 1, 2, …, 5.

The administrative data we have used are derived from the *Continuous Sample of Working Lives* ("Muestra Continua de Vidas Laborales", MCVL), which is a microeconomic dataset based on administrative records provided by the Spanish Social Security Administration. Each wave contains a random sample of 4% of all the individuals who had contributed to the social security system (either by working or being in an unemployment scheme) or had received a contributory benefit (such as permanent disability benefit, an old-age pension, etc.) for at least one day in the year the sample is selected. As a consequence, the sample does not include those individuals without any contact with Social Security in such a year. This may induce a sample selection bias, especially for those unemployed for more than one year but also, for different reasons, for women, immigrants or young workers. In order to circumvent this problem we combined the database for twelve waves, from 2006 to 2017. That is, we kept track of every individual who has had a relationship with the Social Security administration for at least one day during this twelve-year period. For such people, we have a complete labour market history as revealed by the data.

There is information available on the entire employment and pension history of the workers, including the exact duration of employment, unemployment and periods in receipt of disability or retirement pension, and for each period, several variables that describe the characteristics of the job or the unemployment/pension benefits. There is also some information on personal characteristics such as age, gender, nationality and level of education.

Table 1: Shares of the employed workers grouped by level of studies and by age, Spain 2013, 2017

	MEN			WOMEN		
Educational attainment	2013	2017	Variation	2013	2017	Variation
P	9,87	9,05	-8,3%	6,60	5,85	-11,4%
C	20,86	20,88	0,1%	16,06	15,81	-1,6%
S	13,79	13,96	1,2%	12,61	12,90	2,3%
T	8,75	9,27	5,9%	11,45	12,32	7,6%
Age group						
1	3,99	3,82	-4,3%	3,60	3,29	-8,6%
2	12,56	10,77	-14,3%	12,17	10,13	-16,8%
3	16,47	16,09	-2,3%	14,32	14,25	-0,5%
4	13,47	14,23	5,6%	11,12	12,23	10,0%
5	6,78	8,25	21,7%	5,51	6,98	26,7%

Table 1 describes the shares of the different types of workers in 2013 and 2017, grouped by educational attainment and by age (more detailed information appears in Table A1 in the Appendix). It emerges that the largest share of workers classified by educational level corresponds to those with compulsory education (more than 36% in both years), followed by those with secondary education (more than 26%). That is, almost two thirds of the active population have compulsory or secondary education. As far as age is concerned, more than 50% of the active population is between 35 and 55 years old.

There are three main observations that may be drawn from the data in Table 1. First, the active population continues to age as the proportion of young people decreases and the proportion of older workers increases. Second, the average level of educational attainment is increasing. And third, the share of men and women in the active population has remained stable during the period (men accounted for 53.27% of the active population in 2013 and 53.16% in 2017).

The change in the shares of the active population by types depends on both the demographic evolution of the population and the participation decisions of the workers. This latter factor is especially relevant for some types, particularly the younger and older workers with low levels of educational attainment.

For young people, the key element is the decision to continue with their studies, which is sensitive to the economic cycle. Looking at the data of the younger age groups in Table A1 (see the Appendix), it is evident that the reduction in their shares (4.3% for men and 8.6% for women) is distributed very differently by educational attainment levels. By far the largest reduction occurred among those with tertiary studies (more than 30%), probably due to the decision to remain in education. The second largest reduction (about 13%) occurred among young people with lower levels of education. In this case the change may also be related to the lack of motivation they feel towards looking for a job in a competitive world characterised by plenty of higher educated young workers. The opposite pattern appears in young workers with secondary education, who seem to react more swiftly to the economic changes (an increase above 20%).

In terms of older workers, whose shares have increased by more than 20% between 2013 and 2017, it is evident that the higher their level of educational attainment the higher the increase, with a negative variation for those with lower levels of education, who are becoming less and less competitive.

3.1 Employment and duration

We next turn to the situation of the labour market in terms of incidence (employment rates) and intensity (average duration of the workers' employment) for the 40 types of workers considered, for both 2013 and 2017. Tables 2a and 2b summarise the information. The data present a double pattern worth noting. On the one hand, both the incidence and intensity increase with age within each level of educational attainment, for both sexes and the two years. On the other hand, incidence and intensity are systematically larger for those with higher education when comparing groups of the same age (with the exception of young workers with tertiary education).[2] Let us recall here that *incidence* corresponds to the share of workers in the active population who have worked for at least one month during the year, whereas *intensity* is the average number of months in employment of those workers who have been employed for at least one month during the year.

Table 2a: Incidence and intensity of employment by types of workers, Spain 2013

	MEN		WOMEN	
Types	Incidence	Intensity	Incidence	Intensity
P1	0,689	8,299	0,683	8,200
P2	0,755	9,166	0,759	9,432
P3	0,786	9,600	0,810	10,002
P4	0,847	10,337	0,877	10,711
P5	0,890	10,960	0,902	11,114
C1	0,718	8,498	0,718	8,497
C2	0,818	9,968	0,815	10,004
C3	0,851	10,378	0,849	10,375
C4	0,886	10,800	0,884	10,791
C5	0,908	11,139	0,904	11,116
S1	0,669	7,943	0,694	8,041
S2	0,860	10,485	0,845	10,342
S3	0,910	11,056	0,892	10,842
S4	0,933	11,326	0,923	11,195
S5	0,932	11,347	0,935	11,373
T1	0,658	7,213	0,708	7,490
T2	0,895	10,687	0,877	10,442
T3	0,941	11,346	0,920	11,102
T4	0,954	11,505	0,950	11,430
T5	0,955	11,535	0,954	11,564
Weighted mean	0,863	10,479	0,865	10,490
CV	0,113	0,125	0,102	0,118

[2] There is some evidence to indicate that this group of workers is more selective, i.e. less prone to accept jobs that do not fit their aspirations. See for instance Machin & McNally (2007).

Table 2b: Incidence and intensity of employment by types of workers, Spain 2017

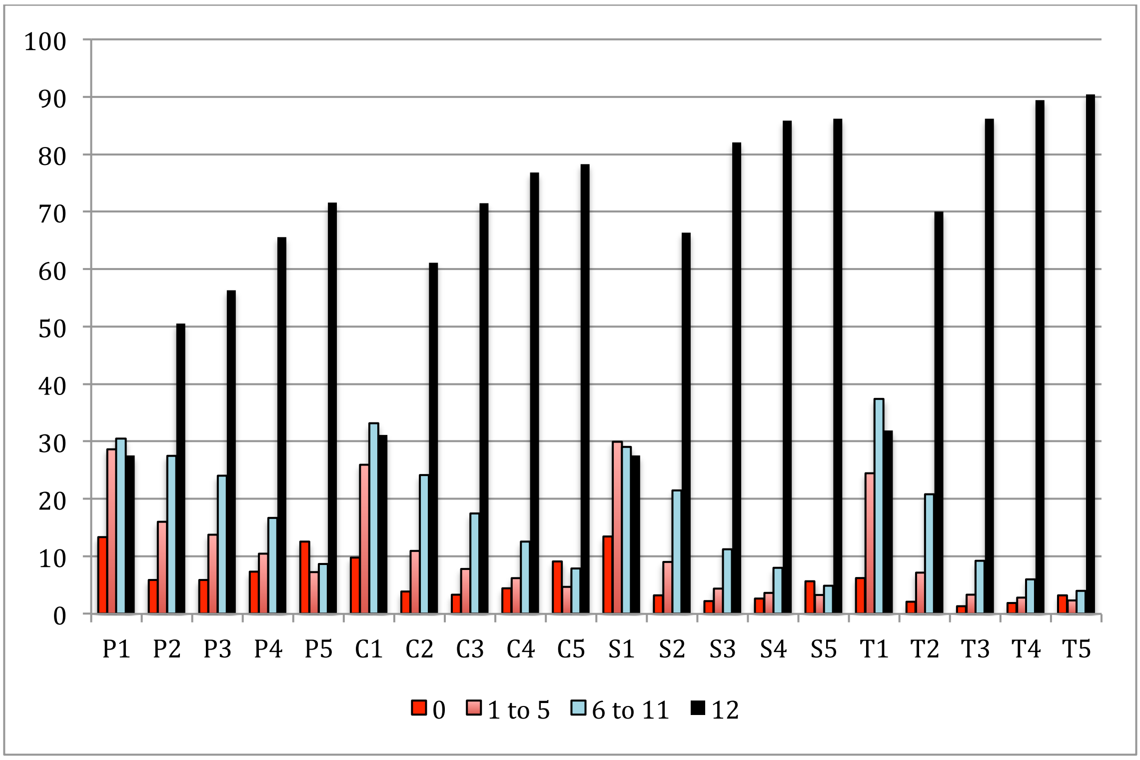
	MEN		WOMEN	
Types	Incidence	Intensity	Incidence	Intensity
P1	0,651	7,761	0,604	7,290
P2	0,793	9,530	0,762	9,245
P3	0,816	9,858	0,800	9,838
P4	0,857	10,400	0,862	10,541
P5	0,895	10,908	0,903	11,028
C1	0,686	8,128	0,660	7,876
C2	0,842	10,208	0,809	9,921
C3	0,884	10,729	0,855	10,414
C4	0,910	11,001	0,892	10,763
C5	0,925	11,239	0,912	11,126
S1	0,667	7,674	0,645	7,318
S2	0,874	10,514	0,845	10,204
S3	0,933	11,257	0,904	10,919
S4	0,947	11,422	0,933	11,241
S5	0,949	11,513	0,943	11,429
T1	0,751	8,459	0,762	8,262
T2	0,901	10,770	0,885	10,501
T3	0,955	11,443	0,936	11,244
T4	0,961	11,563	0,952	11,446
T5	0,966	11,664	0,962	11,595
Weighted mean	0,886	10,683	0,875	10,553
CV	0,114	0,124	0,123	0,134

It is quite apparent that employment rates and employment lengths move in the same direction for all groups (correlation coefficients above 0.98). This feature, rather than making the joint evaluation of both aspects irrelevant, illustrates how the differences between types of workers are accentuated by the combination of those two variables.

The youngest workers educated to tertiary level underwent the largest positive changes between 2013 and 2017, whereas the largest negative changes correspond to the youngest workers with other levels of studies. There are two reasons that may explain these opposing phenomena. First, there has been a substantial reduction in the share of young workers educated to tertiary level, as mentioned above. Second, the data hint at a process of crowding out whereby jobs formerly occupied by less educated workers are now being filled by workers with higher education or more experience.

Figure 1 provides a graphical illustration of the distribution of employment duration by the different types of male workers in 2017. For the sake of visual clarity only four categories have been included: unemployed for the whole period (0 months of work), employed between 1 and 5 months, employed between 6 and 11 months, and employed for all 12 months. It is worth noting that the pictures for women in 2017 and for men and women in 2013 exhibit a rather similar shape. The pattern shows that the older the worker the higher the probability of being employed for 12 months, and the higher the level of educational attainment the larger this probability. The opposite pattern applies to those who are unemployed throughout the whole year. The shares of workers working between 1 and 5 months and between 6 and 11 months are more idiosyncratic. In most cases the density exhibits a U-shaped form with much longer tails than for those in 12 months of employment.

Figure 1: Distribution of men workers by duration, Spain 2017



3.2 Inequality

We now deal with the inequality in the distribution of employment lengths for the different types of workers in the reference years (Table 3). It bears repeating that for each type of worker the vector of employment lengths refers to the whole active population and not only to those workers who were employed during the year (i.e. the length vector will contain zeroes for those workers who were unemployed during the whole period). This is one of the reasons for using the Gini index as the way of measuring inequality.

The data show a consistent pattern that can be described as follows. (1) Inequality is smaller on average in 2017, both for men and women. (2) Women exhibit levels of inequality that are higher than those of men for most types and this is certainly the case for the (weighted) average (4% higher in 2013 and 17% higher in 2017). (3) Inequality decreases with age within each level of educational attainment, except for the oldest workers where age groups 4 and 5 exhibit similar levels of inequality, which may be reversed. (4) Inequality tends to decrease with the level of educational attainment for all corresponding age groups (there is almost a stochastic dominance relationship).

Table 3: The Gini index of employment lengths for the types of workers, Spain 2013, 2017

Type	MEN		WOMEN	
	2013	2017	2013	2017
P1	0,2648	0,2634	0,2756	0,2859
P2	0,1906	0,1804	0,2075	0,2007
P3	0,1530	0,1552	0,1816	0,1636
P4	0,1308	0,1135	0,1015	0,1239
P5	0,1273	0,1222	0,0840	0,1348
C1	0,2472	0,2386	0,2523	0,2424
C2	0,1547	0,0876	0,1518	0,1595
C3	0,0955	0,0698	0,1264	0,0775
C4	0,0710	0,0989	0,0960	0,0970
C5	0,0697	0,0852	0,1180	0,1136
S1	0,2704	0,2725	0,2860	0,2939
S2	0,1187	0,0615	0,1265	0,1346
S3	0,0714	0,0399	0,0917	0,0793
S4	0,0547	0,0468	0,0648	0,0463
S5	0,0532	0,0603	0,0756	0,0608
T1	0,3253	0,3045	0,3026	0,3072
T2	0,1021	0,0946	0,0711	0,1122
T3	0,0528	0,0331	0,0509	0,0595
T4	0,0357	0,0357	0,0462	0,0449
T5	0,0405	0,0449	0,0381	0,0276
Weighted Mean	0,1094	0,0918	0,1138	0,1074

3.3 Welfare evaluation: the three i's of employment

We now apply our welfare measure, as defined by equation [6], to the analysis of employment in Spain in the two selected years. The welfare measure is expressed as the number of months that correspond to the average duration of employment adjusted by inequality, measured by the Gini index.

Table 4 provides an initial approximation of the evolution of employment. It provides the data regarding men and women for all educational attainment levels and age groups (the weighted averages of the corresponding variables). Note that, in spite of the high levels of economic growth and employment creation, the incidence does not improve very much and the improvement in all indices for men is twice that of women. The increase in the employment lengths of the employed workers is even smaller (the increase for men is now three times that of women). The welfare evaluation presents more encouraging results, even though here again men fare much better than women.

Table 4: Average values of employment incidence, intensity and welfare, Spain 2013, 2017

	MEN		WOMEN		Variation 2017/2013	
	2013	2017	2013	2017	MEN	WOMEN
Incidence	0,863	0,886	0,865	0,875	2,67%	1,16%
Intensity	10,479	10,683	10,490	10,553	1,95%	0,60%
Welfare	8,190	8,733	8,163	8,386	6,63%	2,73%

Tables 5a and 5b provide detailed information about the way employment levels and employment welfare are distributed among the different types of workers in 2013 and 2017. We compare relative incidence and relative welfare by normalising the corresponding values, taking the (weighted) averages as equal to 100 for both years. The difference between these two variables is a measure of the impact of intensity and inequality (a sort of "*intensity adjusted by inequality" premium*). The data make it clear that both incidence and welfare increase with age and education. In particular, the larger negative differences between these relative values are found in the youngest age groups (P1, C1, S1, T1). For those educated to primary level only the older workers (P5) present positive differences in 2013, but they become negative in 2017 for all with lower education and also for those in groups C1 and C2. It is also evident that the older and the more educated the worker is, the larger the positive difference. Note that men and women exhibit a similar pattern, but not identical (this will become clear in the next table).

Table 5a: Employment and welfare, Spain 2013

	MEN			WOMEN		
Types	Rel. Incidence	Rel. Welfare	Difference	Rel. Incidence	Rel. Welfare	Difference
P1	79,9	51,3	-28,5	78,9	49,7	-29,3
P2	87,5	68,4	-19,1	87,8	69,5	-18,3
P3	91,0	78,0	-13,0	93,6	81,2	-12,4
P4	98,1	92,9	-5,2	101,4	103,4	2,0
P5	103,1	103,9	0,8	104,3	112,5	8,2
C1	83,2	56,1	-27,1	83,1	55,9	-27,1
C2	94,8	84,2	-10,6	94,2	84,7	-9,5
C3	98,6	97,5	-1,1	98,2	94,3	-3,9
C4	102,6	108,5	5,9	102,2	105,7	3,4
C5	105,2	114,8	9,7	104,5	108,6	4,1
S1	77,6	47,4	-30,2	80,2	48,8	-31,4
S2	99,7	97,1	-2,6	97,7	93,5	-4,2
S3	105,5	114,1	8,6	103,1	107,6	4,5
S4	108,1	122,0	13,9	106,7	118,4	11,7
S5	107,9	122,2	14,3	108,1	120,4	12,3
T1	76,2	39,1	-37,1	81,9	45,3	-36,6
T2	103,7	104,8	1,2	101,4	104,3	2,8
T3	109,0	123,4	14,4	106,4	118,8	12,4
T4	110,5	129,2	18,7	109,8	126,9	17,1
T5	110,6	129,0	18,4	110,3	130,0	19,7

Table 5a: Relative employment and relative welfare, Spain 2017

Types	MEN			WOMEN		
	Rel. Incidence	Rel. Welfare	Difference	Rel. Incidence	Rel. Welfare	Difference
P1	73,5	42,6	-30,9	69,1	37,5	-31,6
P2	89,5	70,9	-18,6	87,1	67,2	-19,9
P3	92,1	77,8	-14,3	91,4	78,5	-12,9
P4	96,8	90,5	-6,3	98,5	94,9	-3,6
P5	101,0	98,1	-2,9	103,2	102,7	-0,5
C1	77,4	48,6	-28,8	75,4	47,0	-28,5
C2	95,0	89,8	-5,2	92,4	80,4	-12,0
C3	99,8	101,1	1,2	97,8	98,0	0,2
C4	102,7	103,3	0,6	101,9	103,3	1,4
C5	104,4	108,9	4,5	104,2	107,2	3,0
S1	75,2	42,6	-32,6	73,7	39,7	-33,9
S2	98,7	98,8	0,1	96,6	89,0	-7,6
S3	105,3	115,5	10,2	103,3	108,3	5,1
S4	106,9	118,1	11,2	106,6	119,2	12,6
S5	107,1	117,6	10,4	107,8	120,7	12,9
T1	84,8	50,6	-34,2	87,0	52,0	-35,1
T2	101,7	100,6	-1,1	101,2	98,4	-2,8
T3	107,8	121,0	13,2	107,0	118,1	11,1
T4	108,4	122,7	14,2	108,8	124,2	15,3
T5	109,0	123,2	14,2	110,0	129,4	19,4

Table 6 summarises the changes between 2013 and 2017 experienced by the different types of workers in terms of both incidence and welfare. The data reveal that changes have affected these types differently and that incidence and welfare have evolved according to different patterns. The table provides some new insights into the dynamics of employment. Young people who lack tertiary education (types P1, C1 and S1) have seen their situation deteriorate. But the youngest with higher levels of education, by contrast, have improved (it is worth recalling here the earlier comment on the specifics of this group). All women with primary education were worse off in 2017 relative to 2013 in terms of welfare and also in terms of incidence for groups P1, P3 and P4 (the other two groups have hardly changed their employment levels). Men exhibit a different pattern, with improvements for groups P2, P3, P4 and P5, both in terms of incidence and even more so in terms of welfare. Young women with compulsory and secondary levels of education are also worse off in 2017 (groups C1, C2, S1 and S2). Here again, men show improvement in the corresponding groups. It is also noticeable that between 2013 and 2017 men improve more than women for almost all of the types, the exception being the T2 and T3 groups for employment, and the S4, S5 and T5 groups for welfare (in all of these cases the data for women is only slightly better).

Table 6: Variation in employment and welfare 2017-2013

Types	MEN		WOMEN	
	Incidence	Welfare	Incidence	Welfare
P1	-5,47%	-11,44%	-11,48%	-22,42%
P2	4,93%	10,48%	0,37%	-0,77%
P3	3,90%	6,41%	-1,20%	-0,68%
P4	1,26%	3,90%	-1,78%	-5,75%
P5	0,57%	0,68%	0,07%	-6,22%
C1	-4,50%	-7,61%	-8,15%	-13,73%
C2	2,85%	13,71%	-0,79%	-2,51%
C3	3,94%	10,52%	0,72%	6,75%
C4	2,71%	1,48%	0,86%	0,48%
C5	1,93%	1,12%	0,83%	1,42%
S1	-0,39%	-4,03%	-7,12%	-16,41%
S2	1,61%	8,50%	0,07%	-2,18%
S3	2,52%	7,92%	1,34%	3,45%
S4	1,54%	3,25%	1,08%	3,49%
S5	1,89%	2,60%	0,85%	2,96%
T1	14,21%	38,07%	7,52%	17,82%
T2	0,75%	2,37%	0,89%	-3,03%
T3	1,53%	4,52%	1,75%	2,13%
T4	0,73%	1,23%	0,24%	0,52%
T5	1,13%	1,79%	0,86%	2,23%

There is another aspect that Tables 5 and 6 illustrate well: taking into account the duration of employment provides a different picture of what has happened during this period in the labour market. In particular the size of the welfare changes is much larger than that of the changes in employment levels.

Figures 2a and 2b provide a graphical illustration of the distribution of the welfare evaluation of employment duration by types in 2013 and 2017, respectively. They enable visualisation of the impact of age and education, how men and women have fared, and how these relationships have changed. In particular the economic recovery has clearly been more beneficial for men and for those workers with higher levels of education, from the perspective of employment.

The most conspicuous feature is the sawtooth shape of the diagrams, which sheds clear light on the role of age in employment. It is also apparent that higher educational levels tend to be associated with higher welfare indices of employment. Another notable feature is that the recovery has been better for men than for women.

Figure 2a: Welfare evaluation of employment by types of workers, Spain 2013

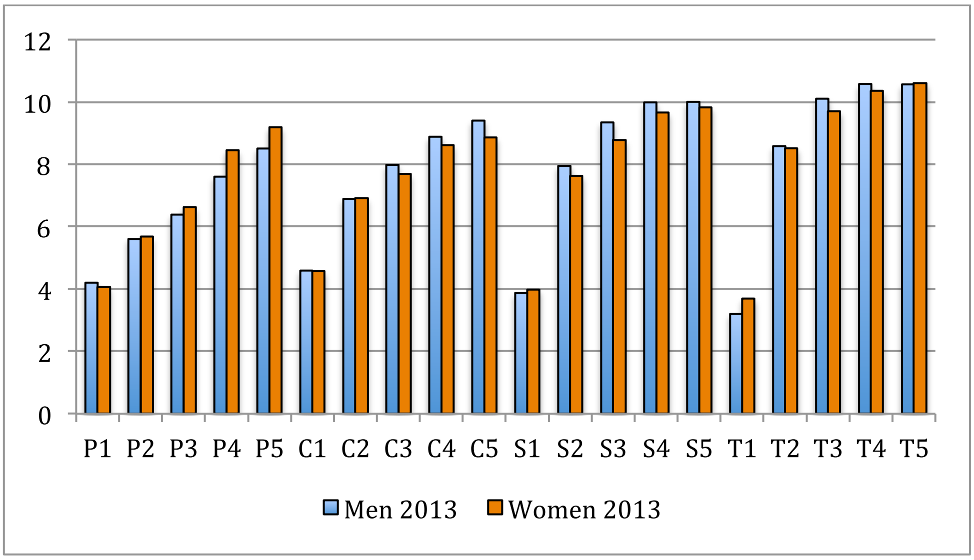
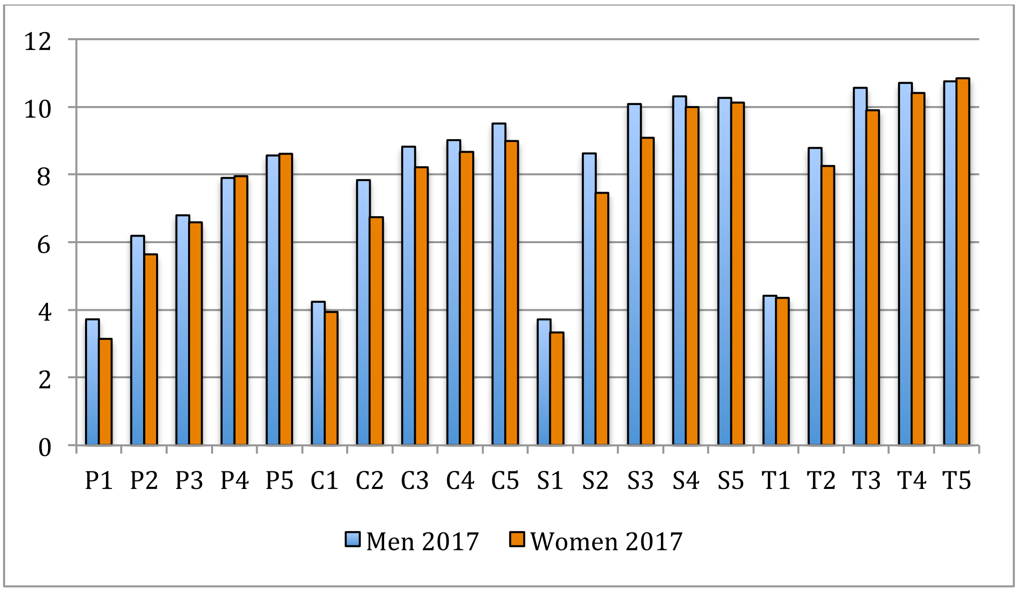


Figure 2b: Welfare evaluation of employment by types of workers, Spain 2017



3.4 The regional perspective

We conclude our analysis by comparing the changes in employment and welfare between the Spanish regions. Now the types of workers are defined just by their geographical location in one of Spain's 17 autonomous regions. It is worth noting here that the regions have many responsibilities in the design and implementation of public policies governing key aspects of social welfare, such as health, education, the provision of social services, and also policies regarding the labour market.

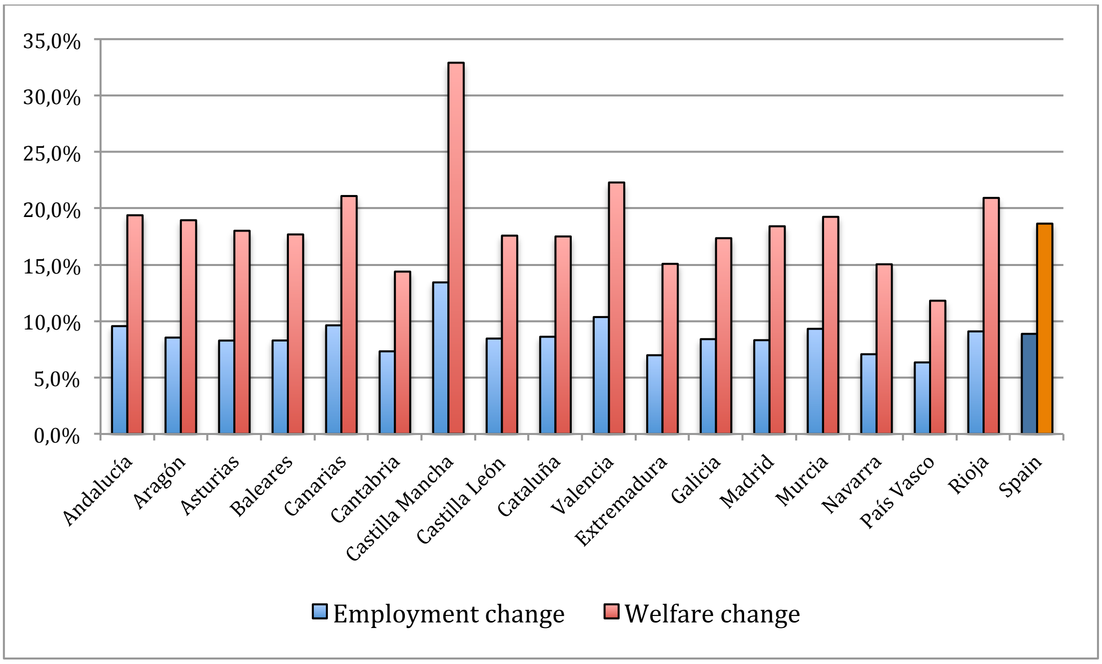
Table 7 presents the summary data for the regions in 2013 and 2017 in terms of both employment levels and employment welfare, normalising the values with respect to Spain, which is set at 100 in each year and each variable. As before, the difference between relative employment and relative welfare provides a measure of the premium by employment length adjusted by inequality. With two exceptions (La Rioja and Cantabria), those regions below (or above) the mean in terms of employment are further below (or further above) in terms of welfare. Andalusia, Castilla la Mancha, Valencia and Murcia are the regions with the largest negative differences, whereas Catalonia, Madrid, Navarra and the Basque Country are those with the largest positive differences. Here again we find that the coefficient of variation is larger for welfare than for employment, with smaller values in 2017 than those of 2013.

Table 7: Relative employment and relative welfare in the Spanish Regions (2013, 2017)

	2013			2017		
Region	Relative incidence	Relative welfare	Difference	Relative incidence	Relative welfare	Difference
Andalucía	95,49	87,24	-8,24	96,09	87,79	-8,30
Aragón	103,72	104,65	0,92	103,41	104,91	1,51
Asturias	102,52	106,19	3,66	101,96	105,62	3,66
Baleares	84,59	81,13	-3,46	84,13	80,48	-3,65
Canarias	95,85	92,01	-3,84	96,52	93,91	-2,60
Cantabria	101,54	102,62	1,09	100,09	98,94	-1,15
Castilla Mancha	93,22	82,21	-11,01	97,13	92,09	-5,03
Castilla León	102,46	105,45	2,99	102,06	104,50	2,44
Cataluña	102,35	108,22	5,87	102,11	107,18	5,08
Valencia	97,14	90,88	-6,26	98,47	93,67	-4,80
Extremadura	96,86	95,02	-1,84	95,17	92,17	-3,01
Galicia	102,00	105,15	3,15	101,56	104,01	2,45
Madrid	104,68	109,97	5,29	104,14	109,75	5,61
Murcia	96,05	91,04	-5,01	96,45	91,50	-4,94
Navarra	104,27	109,64	5,37	102,54	106,31	3,77
País Vasco	108,52	119,20	10,68	106,00	112,33	6,34
Rioja	102,74	100,92	-1,82	102,95	102,86	-0,08
CV	0,055	0,104		0,050	0,086	

Figure 3 completes the picture by illustrating the changes in both variables between 2013 and 2017. Once again, changes in employment and duration are cumulative so that changes in welfare are always larger than those in employment. The Canary Islands, Castilla la Mancha, Valencia and Rioja are the regions with the largest increments. Cantabria, Extremadura, Navarra and the Basque Country are the regions with the smallest variations.

Figure 3: Change in employment and welfare in the Spanish regions, 2013-2017 (%)



4 Concluding Remarks

We have presented in this paper a formula to evaluate the dynamics of the labour market from the employment perspective that synthesises three different dimensions of occupation: incidence, measured by the employment rate, intensity, given by the average length of employment among those in work, and inequality, as measured by the Gini index on the distribution of duration. The advantage of this index with respect to the conventional employment rate is threefold. First, it captures several dimensions that are relevant from a social welfare perspective. Second, it keeps track of the unemployed not only indirectly, as in the employment rate, but also directly through the inequality component, which is defined relative to the whole active population. And third, it provides a different picture of the evolution of employment and new insights on the differences between types of workers and societies.

The empirical exercise illustrates the relevance of these features clearly and shows that the differences between types of workers and regions are much larger when computing the intensity and inequality of employment. The results highlight the role of age and education in the welfare evaluation of employment, as well as the widening gap between men and women induced by the economic recovery.

We conclude by noting that employment rates and employment lengths move in the same direction, thus accentuating the differences between workers and societies, something that emerges clearly from the formula developed in this paper. This feature is not observed when we focus on unemployment, where there are opposing tendencies for some types of workers and regions. This is the case, for instance, for the young unemployed, who exhibit very high levels of unemployment but short unemployment spells. Another interesting case where this occurs is the Basque Country, a region with one of the lowest unemployment rates and the highest average unemployment duration in Spain (see Gorjón, de la Rica & Villar 2018, 2019).

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APPENDIX

Table A1: Shares of the employed workers by types, Spain 2013, 2017

	MEN			WOMEN		
Type	2013	2017	Variation	2013	2017	Variation
P1	0,96	0,82	-14,6%	0,48	0,42	-12,5%
P2	1,92	2,00	4,2%	1,14	1,07	-6,1%
P3	2,16	1,92	-11,1%	1,30	1,09	-16,2%
P4	2,67	2,24	-16,1%	1,88	1,50	-20,2%
P5	2,16	2,07	-4,2%	1,80	1,77	-1,7%
C1	1,66	1,64	-1,2%	1,26	1,18	-6,3%
C2	5,16	4,18	-19,0%	3,93	3,11	-20,9%
C3	6,50	6,44	-0,9%	4,64	4,43	-4,5%
C4	5,32	5,69	7,0%	4,28	4,52	5,6%
C5	2,22	2,93	32,0%	1,95	2,57	31,8%
S1	0,83	1,01	21,7%	0,86	1,07	24,4%
S2	2,93	2,28	-22,2%	3,05	2,26	-25,9%
S3	4,69	4,42	-5,8%	4,40	4,22	-4,1%
S4	3,68	4,04	9,8%	3,13	3,65	16,6%
S5	1,66	2,21	33,1%	1,17	1,70	45,3%
T1	0,54	0,35	-35,2%	1,00	0,62	-38,0%
T2	2,55	2,31	-9,4%	4,05	3,69	-8,9%
T3	3,12	3,31	6,1%	3,98	4,51	13,3%
T4	1,80	2,26	25,6%	1,83	2,56	39,9%
T5	0,74	1,04	40,5%	0,59	0,94	59,3%
Total	53,27	53,16		46,72	46,88	