DISCUSSION PAPER SERIES

IZA DP No. 9135

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June 2015

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

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IZA Discussion Paper No. 9142
June 2015

ABSTRACT

Gender Differentials in Unemployment Ins and Outs during the Great Recession in Spain*

The Great Recession has had a disproportionately negative effect on working men compared to working women in many OECD countries and led to gender convergence in aggregate unemployment rates. In this paper we seek the sources of this recent convergence by using Social Security records on individuals to study the determinants of unemployment ins and outs over the course of a whole business cycle, i.e. 2000-2013. We focus on Spain – a country hit hard by unemployment increases in downturns. Our results indicate that unemployment outs are crucial in understanding changes in unemployment rates in Spain. Furthermore, the huge drop in unemployment outs in the recession, particularly for men, has led to unprecedented levels of long-term unemployment, which has come to account for 64% of total unemployment. Negative state dependence emerges as a key barrier to job access for the long-term unemployed and hence the rate of unemployment is expected to remain high for many years, even if there is a strong recovery.

JEL Classification: J63, J64, J16

Keywords: unemployment gross flows, hazard rates, state dependence, gender differentials

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* De la Rica acknowledges financial support from the Spanish Ministry of Science (ECO2012-35820) and to the Basque Government (IT793-13).

Introduction

Empirical evidence indicates that in economic downturns women exhibit lower job loss and higher job finding rates than men (Sahin et al (2010)). These estimates are based on the general consensus that males are disproportionately represented in highly cyclical sectors, such as construction, whereas women are disproportionately represented in noncyclical ones, such as services (e.g. education and health). With a constant labour supply, aggregate shocks move labour demand relatively more for men than for women, causing a larger outward shift in labour demand during an expansion and a larger inward shift during a contraction. Nonetheless, the 2007 recession had a disproportionately negative effect on working men compared to working women in many OECD countries (Sahin et al (2010), Bachman et al (2012, 2014)) and led to gender convergence in aggregate unemployment rates (i.e Belgium, EEUU, France, Italy, Ireland, Spain). In this paper we seek the sources of this recent convergence by using employer-employee micro-data and analysing individual labour market transitions.

We focus on Spain – a country where the increase in unemployment rates has been particularly strong in the recent downturn and the convergence in unemployment rates by gender has been the largest– and study the trends in unemployment ins and outs by gender covering a whole business cycle, i.e. 1997-2013. Using Social Security records, we take advantage of the information available at individual level to study the determinants of inflows into and outflows from unemployment by gender and by recession (2008-2013) versus expansion (1997-2007). Our final aim is to understand the underlying compositional versus non-compositional elements that explain the intensity of inflows and outflows in unemployment for women and men and their corresponding differences between upturns and downturns of the economy. Though the analysis focuses on Spain, we consider that many of the results obtained can be easily generalized to other continental labour markets where the big recession has led to an important increase not only in the unemployment rate, but more importantly, in the share of long term unemployment. Indeed, nowadays, in EU-28 the share of long-term unemployed is around 45%, and in some countries such as Ireland, Italy, Portugal or Spain is well above 50%). Long-term unemployment in Europe is on the rise and if not fully addressed by policy makers, long-term unemployment will further deteriorate the already bleak job perspectives for many European citizens.

This study contributes to the empirical literature of unemployment ins and outs in two ways: First, it gives a general overview of the effects of the Great Recession on labour market dynamics in a country such as Spain, which has been particularly strongly hit and where job rotation rates are among the highest anywhere (see Bentolila et. al (2012); Bachman et al. (2014)). Other previous studies have also tried to assess – particularly for US-, the extent to which unemployment variation is closely related to unemployment ins versus unemployment outs[1]. To do so we use individual flow data derived from the social security records instead of stock data based on the employment population surveys to construct our transitions rates. We

[1] See Petrongolo and Pissarides (2008), Elsby et al. (2009, 2013), Shimer (2012), Bachman and Sinning (2012), Silva and Vazquez-Greno (2013), Lazear and Spletzer (2012), Barnichon and Figura (2014) among others.

estimate job finding and the layoff hazard rates using individual transitions data conditional on observed individual and jobs characteristics. Typically, previous empirical literature has addressed these questions by using aggregate time series of labour market transitions rather than using a micro-data based analysis. Such approach may not be valid to understand truly the structural frictions when the degree of heterogeneity in the labour market varies a lot, as may be the case in a deep downturn context as the one of the Great Recession. For instance, the aggregate matching function might behave differently when changes in the average characteristics of the unemployed are taken into account.

Our conditional approach is only followed by few recent studies that look at the great recession such as Shain et al (2010) and Bachman et al (2014). However, our analysis departs from theirs basically in the type of data used. We use an employer-employee database taken from the social security records which poses important advantages to the analysed presented. Firstly, we do not suffer from aggregation problems typically found in labour force surveys where only quarterly or annual data is available. Secondly, these survey data are not suitable for comparisons along time since they frequently suffer from methodological changes that might affect the definition of the state of the labour market, particularly, the unemployment state. In relation to the definition of unemployment, this database also allow us to use broader definition of unemployment that differs from the typically used in labour force surveys. The conventional unemployment rate might understate current labour market distress and miss the substantial increase in discouraged workers no longer counted in the labour force as pointed out recently by Kroft et al. (2014) and Song and Von Wachter (2014).

This paper also contributes to the gender differentials literature. Though unemployment variability during the great recession has been largely studied, few empirical papers have addressed the issue of the observed large differences in the ins and outs from unemployment by gender. Hence, our analysis also contributes to the empirical literature concerned with gender differences in labour market dynamics (Sahin et al (2010); Albanesi and Sahin, (2013)). The sharp convergence in the unemployment rate between women and men during the recent economic downturn poses interesting questions for researchers and policy makers, including the role of structural versus cyclical factors in determining the behaviour of the unemployment gender gap. Furthering the understanding of gender differences in labour mobility patterns helps to make it possible to improve the labour market performance of workers in the future. As Smith (2009) highlights, "gendered understanding of the current crisis is important to both understand the likely outcomes and also avoid ineffective policy responses or unintended increases in inequality". For instance, recent empirical work for US shows that male and female unemployment outflow rates have been essentially identical whereas men have faced a much larger increase in inflows.

Our findings indicate the following: First, we confirm the well-established counter-cyclicality of unemployment ins and the pro-cyclicality of unemployment outs (see Blanchard and Diamond (1990), Fujita and Ramey (2009), Bachman et al (2012), among others) but the large increase observed in unemployment rates seem to be more strongly related to a sharp decline in unemployment outs. Second, the decomposition of unemployment ins reveals that during the recession, positive selection in the composition of employed workers, particularly females, smooth the unemployment inflow rate whereas non-compositional effects bring about the cyclical behaviour of the layoff rate. Sectoral composition emerges as one of the most important determinants in explaining changes in unemployment inflows during the recession and also convergence in layoff rates between men and women. Thirdly, we document a huge drop in job access rates in recession as compared to expansion – the decrease reaches 15 pp. for men and 8 pp. for women. In line with previous research (i.e Elbsy et al. 2013; Kroft K. et al. (2014)) we obtain that, among the determinants of this drop, lack of demand and negative state dependence emerge as key sources, which affect men more negatively than women. Furthermore, the decline in unemployment outs has been accompanied by a record rise in long-term unemployment which is likely to generate hysteresis. When hiring rates remain low for a sustained period, job losers are unable to find work quickly and have a much greater risk of becoming long-term unemployed. Indeed, our simulations show that in a scenario of upcoming recovery, unemployment outs will increase for short-term unemployed workers, and in particular, males as they respond more to cyclical forces. On the contrary, long-term unemployed individuals will face enormous difficulties to access a job even in an upcoming expansionary context, as their job access rates remain very low not only in downturn but also in an upturn context. As 64% of total unemployed workers in Spain are Long Term Unemployed, the rate of unemployment is expected to remain high for many years, even in a framework of strong economic recovery. Hence, while the origins of the large recent rise in long-term unemployment are predominantly cyclical in nature, targeted policies to assist the labor market adjustments of the long-term unemployed are likely to be necessary even once a jobs recovery is underway.

The paper is organised as follows: Section 2 briefly presents net employment losses in the latest recessions in Spain by gender and gender differences in trends in unemployment. Section 3 describes the data and Section 4 presents descriptive evidence on job flows from and to employment. Section 5 presents the empirical approach to decompose the observed changes in unemployment ins and outs in recession versus expansion. Section 6 focuses on job loss flows and presents estimates of the determinants of such flows, along with results from the two-step decompositions of changes in the probability of job loss in recession versus expansion and their gender differences. Section 7 focuses on the determinants and gender differentials of job access. Section 8 simulates estimated survival rates in unemployment for different groups of unemployed worker and under different economic scenarios. The aim is to explore the extent to which unemployment outs by gender will react rapidly to an upcoming economic recovery or are expected to remain in the longer term. Finally, Section 9 summarises the results and concludes.

2. **Unemployment Rates and Net Employment Losses by Gender in the Great Recession - Spain**

Figure 1 depicts unemployment rates by gender in Spain since 1976 and reveals that until this last recession, URs have traditionally been higher for females, not only in upturns but also in downturns. However, since the beginning of the last recession unemployment rates by gender have converged. Male unemployment rates experienced a strong increase at the beginning of the recession and since then both series have developed almost identically and experienced the same increasing trend. This convergence in unemployment rates by gender is not observed in previous downturns[2]. Lastly, by 2014, when Spain seems to be beginning to start a new upturn period, there is some evidence that male unemployment rates seem to decrease more rapidly than female ones.

[Figure 1]

On the other hand, Figure 2 presents the proportion of job loss relative to the initial term of the last three recessions in Spain – 1976, 1991 and 2007 – and the time elapsed until the pre-recession employment levels were regained. The current recession is by far the one with the highest rate of job loss – 18% after 23 terms, with a slight recovery from then on.

[Figure 2]

This pattern of job losses changes greatly when relative job loss is disaggregated by gender – see Figures 3A and 3B. In fact, the magnitude of job loss in the 2007 recession for males is 25% at 25 terms after the start of the recession and has started to recover only in the last two terms, whereas for females it is less than 10% relative to the start of the recession and it looks as if the recovery is taking place at a relatively quick pace.

[Figures 3A 3B]

A comparison of these employment losses with those in previous recessions reveals that such differences, although smaller in magnitude, can also be observed in 1991. On the other hand, the intensity of job losses for men and women in the 1976 recession was more similar (note that in 1976 the share of female workers was notably lower than in 1991 and 2007).

In summary, significant gender differences can be seen in (un)employment ins and outs in different phases of the cycle. To understand better the forces that underlie these changes, information is needed on gross flows to and from employment. The next section describes the longitudinal dataset used to study the ins and outs from unemployment.

3. The database: Continuous Working Live Sample (CWLS).

In order to document gender differentials in employment and unemployment outflows and their trends over time, we use the Continuous Working Live Sample (CWLS). This database

[2] The gender differentials observed in unemployment rates in Spain in the course of business cycles cannot be attributed to ins and outs of women to and from the labour market, contrary to what Albanesi and Sahin (2013) find for the US. The female labour market participation rate in Spain has been continuously (and approximately linearly) increasing for females since 1976 to the present (from 30% to 54%), and is uncorrelated with business cycles. This is also confirmed by the empirical study of Bachman and Sinning (2014).

is an event history data set from Spanish Social Security records[3]. It is compiled annually, and comprises a sample of over one million worker case histories (4% of all those registered). For the purpose of this analysis, we combine the annual samples available from 2005-2013. Hence, our initial database includes all individuals who came into contact for at least one day with the Social Security system - either as employees or as recipients of unemployment, pension or disability benefits- at least once between 2005 and 2013. This database provides highly detailed information about workers' past and present labour activities, including contract type, job type, sector of occupation, different kinds of benefits received and reasons for job termination. Individual characteristics such as age, educational attainment levels, household composition and nationality are also available.

We identify the first observation of each individual in the dataset, which corresponds to his/her first employment spell. After the first observation, we follow each worker over time. Hence, we can compile an individual's labour market history at any point in time. Henceforth, the final data used in this analysis cover the working careers of a sample of Spanish workers aged 18 to 64 years over the period 1997-2013.

Two labour market statuses are considered: employed and unemployed, although unemployed here should not be strictly interpreted in terms of the ILO convention – ie. not working, seeking actively for a job and being available to start a new job in 15 days. Register data does not provide information about seeking activities and availability for work although we identify whether an exit from employment implies a transition to OLF (ie, retirement, disability and/or family care). We discard these as employment-to-unemployment transitions. However, and this may be particularly relevant for unemployment outs, some of the unemployed workers considered in our sample might not be actively looking for a job. In this sense, the terms non-employed and unemployed may be used interchangeably in this paper, particularly for the analysis of unemployment outs. Nevertheless, given the depth of the current recession and the increasing incidence of long-term unemployed workers, there is an ongoing debate over how to appropriately measure the state of the labour market. As Song and Von Wachter (2014) states, there is a need to broaden the characterization and behaviour of the group of non-employed workers, not restricting only to those characterized as unemployed by the Current Population Surveys.

The duration of each work spell is based on the start and end dates specified in the contract as provided by the dataset. Likewise, the duration of each unemployment episode is computed by measuring the time lapse between the end date of the worker's previous contract and the start date of the new one. This is particularly relevant for our purposes. In most studies the information provided is either annual or quarterly, i.e. information relating to individual labour market transitions over the course of an entire year or quarter. As a result, these studies tend to under-represent the real number of short-term transitions within any given period. Other important advantage of using social security records versus the current population survey or registered unemployed is that we do not suffer from differences in the pool of unemployed or employed due to survey redesigns. Moreover, since our data are

[3] See García-Perez (2008) for a detailed description of this database.

derived from social security registers, our measures are not affected by measurement issues related to self-reporting of labour force status or unemployment duration and hence, they are comparable over time[4].

Unemployment as a status includes registered unemployment either receiving benefits or not, and we control whether an unemployment in is due to a layoff or a quit. Our dataset allows us to compute not only the period of unemployment during which workers are covered by UIB (either contribution-based or assistance benefits) but also the period after benefits expire. This poses a great advantage as compared with other administrative datasets, like the one used by Petrongolo and Pissarides (2006) for Spain, where the unemployment period is truncated at the point when benefits run out.

We track each spell of employment and unemployment to the point of transition or to the end of the observation period (December 31 2013). In the case of employment, there is information on the reason why the job is lost so each uncensored job spell can be identified as either a layoff, a quit, a transition to OLF (i.e retirement, disability, etc), or a job-to-job transition. We include transitions with an observed unemployment spell of 15 days or less as job-to-job transitions[5]. Similarly, for the case of unemployment (non-employment) each uncensored spell can be identified by the kind of job that each worker finds as well as to transitions to retirement or disability.

Although the information is provided on a daily basis, for sample size reasons, the final dataset is build using the quarter as the reference unit of analysis[6]. This decision does not introduce significant biases in our analysis due to aggregation problems because we have precise information on the individual tracks within each quarter. For instance, there are many consecutive short term employment spells in our database and they tend to take place at the same firm. We have aggregated them in one single employment spell whenever they are separated by a short episode of unemployment (no more than 15 days). This notably reduces the proportion of workers who have more than one spell of employment in a single quarter, but does not rule out this possibility. Hence, in those cases, we take the longer employment spell –as well as the longer unemployment spell- per individual and quarter.

Given this sample selection criteria, our sample consists on 1.676.144 unemployment spells. Of these, 49.2% correspond to female workers. With respect to employment spells, the sample consists of 3.312.736 observations, 46% of which corresponds to female workers.

[4] The Spanish current population survey has suffered different methodological variations along the time-period covered in this paper (i.e changes on the survey design in 2002 or changes on the reference sample in 2013).

[5] To avoid odd behaviour in the estimated baseline hazard functions due to the scarcity of observations spanning longer durations, when estimating the model we right-censor any observed spells of unemployment of 48 months (16 quarters) or longer and any observed spell of employment of 240 months (60 quarters) or longer.

[6] A monthly spell database becomes extremely demanding from the computational point of view given the long time span considered in the paper, i.e. 1997-2013. Some estimations, such as that of the layoff probability by gender within detailed cells (sector-contract-skills) and the Oaxaca decomposition prove unmanageable with monthly spells. Nevertheless, as robustness checks we compare the results using monthly versus quarterly transitions when possible but we do not find any qualitative differences with respect to the determinants of gender gaps in job loss or job access.

4. Unemployment Ins and Outs – Descriptive evidence

In this section we present annual average of quarterly gross flows using the sample from the social security records described above.

4.1 Unemployment Ins – Layoffs

Figure 4 describes annual averages of quarterly unemployment inflows from 1997 to 2013[7]. Given the strong duality of contract types in the Spanish labour market, we separate these ins not only by gender but also by type of contract. The first point to be made is that most unemployment ins involve workers on fixed-term contracts. Flows from indefinite contracts are very unlikely and the change observed in 2008 is relatively low when compared with flows from fixed-term contracts. Second, for both males and females, unemployment ins are pro-cyclical, particularly among those with fixed-term contracts. This is because the vast majority of new job needs are covered with new fixed-term contracts which exhibit high and possibly increasing rotation in downturns as a result of shorter terms. Third, women experience higher rates of unemployment inflows than males up to 2007, but from then on the intensity is reversed, especially among workers with fixed-term rather than indefinite contracts. However, from the start of the recession onwards the layoff probability for women increases less than that for males, who prior to the recession were on average in jobs/contracts with lower rotation rates.

[Figure 4]

Job separation probability is expected to be greater in labour markets with higher levels of flexibility, such as the UK or the US, but Figure 4 shows that job separation probability is also high in Spain. As Silva and Vazquez-Grenno (2013) document, transition rates from permanent employment to unemployment in Spain are very low, even under the downturn period, but the prevalence of temporary contracts have raised unemployment ins in Spain so that overall transition rates are even higher than those exhibited by the UK. These results are consistent with those found by Elsby et al (2010). When comparing Spain with the US, these authors reveal that job separation probabilities were about the same in the two countries during the downturn. Furthermore, in the two countries, the increase in job separation rates was mainly driven by a strong increase in the job separation rates for men (from 3% to 4%) and male workers faced a much larger increase in inflows in the current recession than females.

4.2. Unemployment Outs – Job Access

Figure 5 depicts annual averages of quarterly unemployment (non-employment) outflows for the period 1997-2013 by gender. As before, we separate access to employment via fixed-term jobs from access via indefinite contracts. The rate of access to indefinite

[7] We restrict our study to those who experience a layoff, which fits the concept of job loss better. Moreover, the contribution of quits to the dynamic of the unemployment rate and to the dynamics of the gender gap in the unemployment rate is negligible.

contracts is lower than 1% and has been decreasing steadily since 2007. Although the rate of access to fixed-term jobs is quite substantial, the drop since 2007 is worth noting: it is particularly strong for men, at about 13pp – down from 30% in 2007 to 17% in 2008.

[Figure 5]

This scenario is fully consistent with the trend in unemployment rates seen earlier. Before 2008, unemployment rates among women were higher than among men as women were more exposed to layoffs as a result of their higher proportion of fixed-term contracts, their shorter contract duration and a lower rate of employment inflows than males. However, from 2008 onwards, two facts emerge simultaneously: on the one hand women are slightly less exposed to layoffs than males; on the other job access by gender converges. As a result, unemployment rates by gender start to converge from 2008 onwards. In the sections below we decompose the underlying factors for unemployment ins and outs into compositional versus non-compositional factors in an attempt to determine their relative importance and hence help to understand what is behind these gender differentials.

To put the results in an international context, the Spanish worker flows, as other continental European countries, are characterized by lower values of the job finding and separation rates than the ones computed on US data (Elsby et al. 2013). For instance, Shimer (2012) find a job finding probability of around 30% and a separation probability of around 2%. Using the LFS, the French job finding probability amounts to 7.5% whereas the separation probability is 1.22%.

The trends just presented for the current big recession are not exclusive of the Spanish economy. For instance, the decline in the job finding probability from peak to trough during the recession of 2007 in US, though it was similar for men and women, it was around 20 pp. (from 40% to 20%). However, we should note that determinants of gender differentials in the unemployment rate in Spain might be different from those found in US since the gender gap differential observed in the downturn in US is mostly explain by differences in the behaviour of the job separation probabilities and not on job finding probabilities (Sierminska and Takhtamanova (2011)).

Lastly, given that unemployment ins and outs remain relatively constant in the years of expansion and recession respectively, from now on we divide the whole analysis into two periods: the upturn[8] (2000-2007) and the downturn (2008-2013). Our empirical strategy consists of estimating the determinants of unemployment ins and outs in expansion and recession periods (separately for men and women) and then, break the average differentials in predicted flows down into characteristics (composition effects) and difference in coefficients (non-compositional or behavioural effects).

4.3 The contribution of Unemployment ins and outs to the Unemployment Rate

[8] Though in the statistical section we have shown the timer interval 1997-2013, in the estimation we will restrict the analysis for the upturn to the years 2000-2007. Hence, our sample contains seven years for the upturn and six years for the downturn.

In this sub-section we seek to document the extent to which the recent upswings in unemployment shown in Figure 1 are due to increases in unemployment ins and/or to declines in unemployment outs.[9] This analysis is based on the dynamics of steady state unemployment (u^{ss}).

$$u_t^{ss} = \frac{\lambda_t^{EU}}{\lambda_t^{EU} + \lambda_t^{UE}} \qquad [1]$$

We adopt the same notation as Shimer (2012) and the term λ^{EU} represents the instantaneous probability of finding a job and λ^{UE} the instantaneous probability of losing a job. Based on US data, Shimer (2012) shows that Equation (1) provides a very good approximation of the end-period unemployment rate since the correlation between u^{ss} and the observed unemployment rate was 95% for the last two decades. For Spain, the correlation between the observed unemployment rate and this hypothetical unemployment rate computed using the ins and outs of unemployment is 97% for men and 94.5% for women during the analysed period. We consider that they are both high enough to justify the use of the steady state approach to examine the relative contribution of the separation and the finding rate to unemployment fluctuations.

In order to provide a single measure of the contribution of each rate to the changes in unemployment there are two main approaches which lead to very similar results (Shimer (2012) versus Petrongolo and Pissarides (2008) or Elbsy et al (2013)). They both are based on computing the following hypothetical unemployment rates:

$$u_t^{ss\_EU} = \frac{\lambda_t^{EU}}{\lambda_t^{EU} + \overline{\lambda}^{UE}} \qquad [2]$$

$$u_t^{ss\_UE} = \frac{\overline{\lambda}^{EU}}{\overline{\lambda}^{EU} + \lambda_t^{UE}} \qquad [3]$$

With equation (2), we hold the job finding probability rate constant and its historical values and hence, we measure the contribution of the separation rate to the fluctuations in unemployment. Similarly, in equation (3), we hold the separation rate constant and we measure the contribution of the job finding probability to fluctuations in unemployment.

In the following lines we follow the approach used in Petrongolo and Pissarides (2008) and Elbsy et al. (2013) to compute the relative contribution of the two transition rates. Basically, the idea is that to compare changes in inflow and outflows rates on an equal footing

[9] A long line of research on labour market flows prior to the last two recessions came to the conclusion that cyclical ramp-ups in unemployment are driven by both margins. More recently, Shimer (2007) concludes that fluctuations in the employment exit probability are quantitatively irrelevant in the last two decades. Instead, increased unemployment duration and a decline in the rate at which workers flow out of the unemployment pool are advanced as arguments driving all contemporary unemployment variation. The current downturn provides an opportunity to assess these conclusions.

with respect to changes in unemployment, all one needs to do is compare the logarithmic variation in each of the flow hazards. We use 2007 as the reference year and compute the cumulative logarithmic difference in inflow and outflow rates relative to this reference year. The results are presented in Figure 6. The figure suggests that inflows account for a substantial fraction of unemployment variation but only in the early stages of the downturn, whereas the contribution of the outflow rate becomes more dominant as the downturn continues. This result is in line with Shimer (2012) for US and Hairault et al (2015) for France, but is in opposition to the conventional wisdom built around the research by Darby et al (1985), Blanchard and Diamond (1990), and Davis and Haltinwager (1990) that recessions are period characterized primarily by a high exit rate from employment. Elbsy et al. (2013) find that both, ins and outs are important in a complete understanding of cyclical unemployment for continental Europe (France, Germany, Spain, Italy) whereas for Anglo-Saxon countries (Australia, Canada, New Zeland, the United Kindom and the United States) the variation in the outflow rate accounts for the majority of the variation in the unemployment rate. Silva and Vazquez-Greno (2015) in a three state labor market model –inactivity is included-, also find that both job finding and job separation rates are important in accounting for the volatility in the Spanish equilibrium unemployment rate. Interestingly, the transition rates involving inactivity make a quantitatively minor contribution to the fluctuations in unemployment[10].

[Figure 6]

Nevertheless, as before, there are gender differences which are worth highlighting: using the method presented in Elbsy et al (2010) and Shimer (2012) unemployment outs account for around 90% of the fluctuations in the unemployment rate for women, compared to around 70% for men. Hence, fluctuations in the unemployment-to-employment transition rate are far more important than employment-to-unemployment fluctuations for explaining the recent movements in the unemployment rate for men and women. This will be used in the last section in the paper, as we will focus on unemployment outs rather than on unemployment ins when we speculate about the prospects of Spanish unemployment levels in an upcoming recovery setting.

5. Two-Step Blinder-Oaxaca Decomposition in Unemployment Flows - *Empirical Approach*

So far we have presented an unconditional analysis of the dynamics of the job separation and job finding transition rates by gender. To dig deeper into the determinants of these dynamics we estimate these transition probabilities and apply a two-step Blinder-Oaxaca decomposition for each transition, trying to identify whether differences in coefficients (non-compositional effects) versus changes in the characteristics (compositional effects) drive the

[10] Nevertheless, the comparison of our results from those presented in Silva et al (2015) must be taken with caution for two main reasons. Firstly, the type of data used is different since typically these papers used time series aggregate data instead of micro data. Secondly, the period covered in their analysis differ from the one contained in this paper. In particular, with a few exceptions, these papers stop their analysis at years 2009-2010 when we were still in the middle for the current recession. Our paper presents the analysis for unemployment flows until December 2013, the end of the recession. This last difference is particularly important since it is well establish that to explain unemployment variability, the ins in unemployment are far more important at the beginning of the recession where the outs from unemployment are more important at the end of the recession.

observed trends. To address the empirical estimation of job separation and job finding probabilities we estimate hazard rates so as to best gauge the relevance of state duration dependence in explaining the behaviour of job separation and job finding probabilities. This is particularly important for the latter, and cannot be assessed with the use of time series data, where individuals are not followed over time and hence, job finding probabilities conditional on unemployment duration cannot be properly estimated.

In the following lines we describe the approach followed to execute the two-step Blinder-Oaxaca decomposition for the state of unemployment, but the analysis for the employment state is performed equivalently. In order to decompose the determinants of changes in the unemployment exit probability by period (recession versus expansion) and by gender, we use the following two-step strategy[11]:

First Step: Estimate the individual hazard rate (*h(t)*) of unemployment. To estimate the discrete-time duration model, we can construct a panel dataset such that the spell length of any given individual determines a vector of binary responses. Let y_i be a binary indicator variable denoting transitions to potential destination states upon exit, that is, for the pool of unemployed, $y_i=1$ if individual *i* transits from unemployment to employment and zero otherwise. Hence, we end up with a binary panel data set which can be estimated using binary models (Jenkins (2005)), where we estimate the probability of an event taking place:

$$h(t/\Omega) = F(\alpha + \gamma h_0(t) + \beta Z(t) + \delta J(t) + \varphi A(t) + \varepsilon(t)) \qquad [4]$$

The term $h_0(t)$ stands for the duration dependence term. The set of covariates $Z(t)$ represents individual characteristics, $J(t)$ represents job characteristics, and the term $A(t)$ contains cyclical information. Within individual characteristics we include age (three categories), nationality, family composition, labour market experience, the receipt and length of unemployment benefits, and educational attainment levels (three levels). Within job characteristics we include sector of activity (15 sectors), type of contract (permanent contract, intermittent contract, temporary contract and part-time contract), whether the worker was hired by temporary help agency, whether the worker was recalled, job qualification (10 categories), firm`s ownership (public versus private) and firm´s size (four categories). The business cycle is represented by the rate of growth of the quarterly GDP and with regional dummy variables. These covariates are common to the unemployment and employment hazard rate except for those related to the unemployment benefit system, which are only considered for the case of the unemployment state. We specify the duration dependence of the hazards using a set of dummy variables (five dummies for the unemployment hazard and six dummies for the employment hazard).

[11] This two-step decomposition can be thought of as a variant of the decomposition in Juhn et al (1991). Juhn et al (1991) first decompose gender differentials at a point in time and then look at the changes in those differentials over time. We follow this approach because we consider that the main driver of gender differentials in unemployment flows is the differences in their behaviour in the two different periods.

Commonly, the link function *F* is the logit or the conditional log-log function, but in our empirical exercise the execution of the Blinder-Oaxaca decomposition lead us to use the linear probability model instead[12]. The Blinder-Oaxaca decomposition suffers from an identification problem when dummy variables are included in the model and this affect the interpretation of the decomposition[13]. To solve this identification problem, we use the variant introduced by Gardeazábal and Ugidos (2005) (henceforth GU) who solve it by introducing a normalising restriction on the coefficients of the dummy variables which rests on the linearity assumption. In addition, as shown by Fortin et al (2011), linearity assumptions prevent path dependency.

Once Equation [4] is estimated for the two periods under consideration and for men and women separately, the first-step decomposition consists of separate decompositions by gender (*g=f, m*) of changes in average (un)employment flows between recession and expansion, the Oaxaca-Blinder decomposition will be (for ease of exposition, assume that X contains all the covariates used in the estimation):

$$R_g = \left(\overline{h}_{t_1 g} - \overline{h}_{t_0 g}\right) = \left(\overline{X}_{t_1 g}\hat{\beta}_{t_1 g} - \overline{X}_{t_0 g}\hat{\beta}_{t_0 g}\right) = \left(\overline{X}_{t_1 g} - \overline{X}_{t_0 g}\right)\hat{\beta}_{t_1 g} + \left(\hat{\beta}_{t_1 g} - \hat{\beta}_{t_0 g}\right)\overline{X}_{t_0 g} = \overline{E}_g + \overline{C}_g \quad [5]$$

Where R_g refers to the "Raw" difference in the unemployment transition probability in a upturn (t_1) versus an downturn (t_0) for gender *g.* The term E_g denotes differences in the average predicted transition rate (recession versus expansion) due to differences in endowments (composition effect) whereas C_g captures differences in the transition probability between the contraction and expansion periods due to differences in the coefficients, i.e. in the impact of the covariates which capture differential in returns or market values for the same observed characteristics –non compositional (sometimes denoted by "behavioural") effects.

Second Step: We decompose the gender differentials in the observed changes in recession versus expansion. This Double Difference Decomposition consists of taking the average gender differences in the changes in unemployment exit probability obtained in the previous step (R_f - R_m) and further decomposing them into composition and non-compositional effects. The decomposition of this double difference is achieved as follows:

$$R_f - R_m = \left(\overline{h}_{t_1 f} - \overline{h}_{t_0 f}\right) - \left(\overline{h}_{t_1 m} - \overline{h}_{t_0 m}\right) = \left(\overline{E}_f + \overline{C}_f\right) - \left(\overline{E}_m + \overline{C}_m\right) \quad [6]$$

With this second decomposition, we will be able to identify whether differences in coefficients versus compositional effects matter more to explain the observe convergence in layoffs and unemployment exit rates.

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[12] Bachmann and Sinning (2012) also use the linear probability model in order to apply the Oaxaca-Blinder decomposition on the estimated transition probabilities. Nevertheless, as a robustness test, we also estimate the hazard rates using the conditional log-log function which is the standard link function for discrete time duration models. We can not compare the detailed decomposition but we do compare the aggregate decomposition one and very similar results are obtained.

[13] A problem related to the detailed decomposition of dummy variables is the arbitrary choice of the reference categories that are omitted from the regression model.

6. Decomposition of Estimated Unemployment Ins and Gender Differentials – Results

Before presenting the results from the estimation and the subsequent decomposition, Tables 1 and 2 present the distribution of employment spells and layoff rates by gender and other job and individual characteristics, respectively. Upturn and downturn periods are presented separately to show the extent to which the observed distributions change in different phases of the business cycle. The following interesting issues arise from table 1:

- The recession has led to a change in the composition of job spells, making them more stable, given that the share of long tenure job spells, with indefinite contracts located in medium and large firms that require higher skills has increased whereas the share of short-duration fixed-term jobs that require lower skills has decreased notably. This is because layoffs, mainly those at early stages of the recession, have been concentrated in low-skilled, short-duration jobs associated with fixed-term contracts. The main difference between men and women seems to be that layoffs from these low quality jobs have been more intense for men.
- The presence of workers under 30 and those over 45 in the employment spells is significantly smaller in the recession than in the expansionary period. For the under 30s this is mainly due to their higher incidence in layoffs in the recession due to the fixed-term nature of their contracts. For the over 45s it is more a result of how extremely hard they find it to secure another job after a layoff. This decrease is greater for men than for women.
- The incidence of fixed-term contracts in the pool of employment spells decreases in the recession given that workers with such contracts are the first to be laid off during that period. Interestingly, the proportion of part-time contracts increases for both women and men.
- By sectors, in the recession there is a significant decrease compared to the expansion in the incidence of employment spells in male dominated activities such as construction (from 16% to 12% for men) and industry (from 24% to 21% for men and from 11% to 8% for women) and a corresponding increase in some female dominated activities in the service sector, such as commerce, hotels, education and health.

[Table 1]

Furthermore, table 2 points out the following facts concerning the characterisation of layoff rates:

- Female layoff rates are consistently higher than male ones in the period of expansion. This trend is reversed in the recession, when layoff rates for both genders converge to almost the same level. Indeed, average layoff rates in the recession fall very slightly for women in comparison to the expansionary period but increase by around 1.7% for men. It is interesting to highlight that data reveal that we can say that for men, the increase in the layoff rates during the crisis has been an “aggregate phenomenon” but this is not so clearly observed for males.

- A look at changes in the layoff rates of women and men for different demographics and job types reveals a great deal of heterogeneity between different groups. Unemployment inflows increase more for men than for women, particularly in low-skilled jobs with fixed-term contracts at small firms, and for workers with low educational attainment levels. Interestingly, the same goes for men in the public sector, among whom layoff rates increase by significantly more. For instance, for men with fixed-term contracts the layoff rate rises from 16 to 22%, whereas the increase for women is only 1 pp. Secondly, for men the layoff rate increases only slightly in all sectors except construction, where the increase is very strong (5.5 pp). However, for women there is a decrease in the layoff rate in many sectors when the recession period is compared to the expansionary one. Thirdly, the layoff rate for men in very small firms increases substantially in the recession (from 8.8% to 11%), whereas for women the increase is smaller (from 8.6% to 9.8%). Finally, a look at changes in the layoff rate by occupation reveals that in low-skilled occupations (clerical assistants, class 1 & class 2 officers and class 3 officers) men experience a substantial increase in layoff rates in the recession period (from 7.7% to 10%). Again, the increase is smaller for women.

[Table 2]

Two-step Decomposition – Results

The decomposition method described in the previous section allows us to examine the contribution of compositional versus non-compositional effects to variations in the layoff probability between the upturn and the downturn. Results from the estimation of equation [4] for the two periods under consideration and for men and women separately can be found in Table A.1. Once the GU identifying correction is applied, the two-step decomposition of average differentials in predicted layoff rates given by these estimations – equations [7] and [8], is presented in Table 3.

[Table 3]

The first four columns present the absolute and relative contributions of composition and non-compositional effects of each covariate to differences in unemployment ins in the downturn compared to the upturn for each gender separately – equation [7], first-step decomposition. The last two columns decompose gender differences in differences in layoffs (recession versus expansion) into composition and non-compositional effects – equation [8], second-step decomposition.

The layoff rate is observed to be higher in the recession than in the expansion, which is in principle, the expected cyclical response, but the raw differential in layoff rates is almost negligible (0.00045) for women whereas it stands at 0.0149 for men. Turning to the first-step decomposition, it can be seen that for both men and women composition effects seem to lead to a decrease in predicted layoffs whereas differences in coefficients seem to lead to the opposite[14]. Table 3 reveals that compositional changes seem to lead to a large decline in the

[14] Using the conditional log-log function to estimate the employment hazard rate, the compositional effects are estimated to be -0.0257 for females and -0.0171 for males whereas the differences in coefficients are estimated to be 0.0262 and 0.0337, respectively.

layoff rate (of around 2 pp. for women and 1.8 pp. for men). Hence, the current crisis has led to a substantial change in the composition of employment: Workers who kept their jobs during the recession are those with higher human capital and high quality jobs and more stable contracts (i.e holding permanent contracts) in medium or large firms, which explains their lower layoff rates in this period compared with the expansionary one. Similar evidence is shown in Bachmann and Sinning (2012) for the US[15]. The composition of employment has also changed in terms of skills and sectors of activity although the overall impact of these factors on the composition effect is lower[16].

Interestingly, the GDP growth rate contributes negatively for men (-20.3%) though not for women whose contribution is positive but small (4.4%). Note that this is due to the fact that women already experienced high levels of job rotation during the expansion as it was shown in Figure 4. Hence, for men we obtain the expected cyclical response, that is, layoffs rates would have decrease more as a result of the large drop in the economic growth.

By contrast, the change in the coefficients for the same characteristics seems to have led to a large increase in the layoff rate of 2 pp. for women and 3.5 for men. This is because job characteristics, such as the type of contract (temporary contracts), firm size (working in small firms), working in the public sector, and individual characteristics such as education (low educated) and tenure (short-term jobs) are less effective in preventing layoffs during the downturn than during the upturn[17]. There are other covariates, such as sector of activity, whose effects are also important but they have asymmetric impact on the layoff rates between men and women and will be commented later on. Given that the overall effects due to differences in coefficients are significantly greater for men, the higher increase in the layoff rates for men than for women observed in the recession cannot be exclusively linked to compositional factors but rather to non-compositional factors, as changes in coefficients play a major role.

Finally, looking at the decomposition of gender differentials of these differences, as revealed by the second-step decomposition (columns 5 and 6 in Table 3), a decrease of 1.5 pp can be seen in the observed gender differentials. This means that there is convergence in layoff rates between women and men in the recession compared to the expansionary period. Composition effects explain only around 18.7% of this convergence. However, differences in coefficients are relevant for explaining the decrease observed in gender differentials with respect to changes in layoff rates (81.3%). In term of job characteristics, the main determinants are sector of activity (69.8%) and, to a lesser extent, firm size (21%), education

[15] Bachmann and Sinning (2012) find for the US that shorter tenure jobs are less stable, so increases in job tenure reduce unemployment inflows in recessions. Similarly, highly educated workers are more likely to keep their jobs in a recession than less educated ones, so increases in education reduce layoffs in recessions. However, these authors do not explore gender differences in unemployment inflows.

[16] We obtain that for men the drop in share of jobs in the construction sector explains 6.3% of the compositional component.

[17] Within brackets we displayed in the text the covariates more relevant to understand the results obtained. They are derived from a detailed decomposition made by each covariate. This detailed is not shown in the article for sake of concreteness but they are offered upon request.

(15.6%) and job qualifications (11%)[18]. In terms of sectors of activity, construction plays a key role since a detailed decomposition analysis reveals that it explains around 23.5% of the narrowing in the gender gap in layoff rates. Sector of activity is undoubtedly the main driver in explaining the decrease in gender differentials in layoffs and is closely linked to the increase in layoffs of male (and not female) workers from the construction sector in the recession compared to the expansionary period. This is consistent with the facts depicted in Table 2, where it can be seen that the risk of layoff for men working in the construction and in industry is notably higher in the recession than in the expansionary period. However, for women the risk of layoff from construction increases only very slightly when comparing both periods.

To summarize, overall, unemployment ins have remained barely constant for females but rather have increased by around 1.5 pp for males. This different behaviour has led to a convergence in layoff rates by gender. To understand this process, the first issue to point out is that the current crisis has led to a substantial change in the composition of employment: Workers who kept their jobs during the recession are those with higher human capital and more stable jobs. This positive selection in employment has been stronger for females than for males, which explains a (small) fraction of the observed convergence in layoff rates mentioned before – around 19%. Second, job characteristics, such as temporay contracts, working in the public sector, and other individual characteristics such as low tenure and low-education increase the layoff probability in the downturn relative to the upturn. This last effect is stronger for men than for women. In addition, the end of the housing boom has led to a sizable number of layoffs for workers in the construction sector, and men have been hit particularly hardly. These forces are the main drivers in explaining the decrease in gender differentials in layoff rates.

7. Decomposition of Unemployment Outs (Job Access) and Gender Differentials – Results

Let´s turn now to the analysis of the unemployment outs. Descriptive statistics for job access are presented in Table 4. The first point to be made is that during the last recession the quarterly job finding rate dropped from 36% to 21% for men and from 32% to 23% for women. Hence, the average job finding rate was higher for men than for women in the expansion. But since 2008 the situation has been reversed: women have slightly higher exit rates from unemployment. The drop in the probability of finding a job is concentrated more among young and low-qualified workers coming from small firms, with fixed-term contracts. This finding is common to women and men. In terms of sectors of activity, Table 4 reveals that men experience larger drops in job finding rates than women in almost all sectors, although the differences are greatest in the construction sector, where the drop is from 44% to 21% (23 pp) for men, but from 24% in expansion to 13% in recession (7pp) for women. In industry, the drop in the exit rate from unemployment is around 15pp for men and 11pp for women.

[Table 4]

[18] Indeed, when we look at the detailed composition for men we see that the contribution to the increase in the layoffs rates obtained due to difference in coefficients is closely related to low educated workers with low job skills in small firms. That is, in the recession men located in these jobs are less protected from being layoff and in the expansionary period.

There are also interesting differences in the job finding rate by occupational groups. In particular, the difference between women and men in the probability of exiting unemployment is at its largest -around 8pp- for low-skilled occupations such as first, second and third class clerical officers during the expansionary years. However, these differences disappear with the recession due to a large drop in the job finding rate for male workers (around 16pp, compared to around 8pp for women). Notice that unemployment is more intense for men in these occupational groups and that the proportion of women is lower than in other skill groups .

Two-Step Decomposition – Empirical Results

In the conditional analysis we present below we want to assess whether the drop in the job finding probability in the downturn relative to the upturn is due to changes in the composition of the unemployed pool of workers or rather to variations in the speed of exit from unemployment for an individual with a given set of characteristics. As in the previous section, we first estimate separately the hazard rate –unemployment- for women and men and for expansion and recession, respectively. The results of these estimations are displayed in Table A.2. The estimate of the Job Finding probability includes not just individual characteristics but also previous job´s characteristics as well as their situation with respect to the UB system – in particular, whether the worker receives unemployment benefits and the length of the entitlement and whether the worker receives assistance benefits. Though not shown, we have also estimated the same model but restricting the sample to workers aged 25-55 years old, which are highly attached to the labour market. Results are almost identical so we do not report them although are available upon request.

The results of the two-step decomposition of the average probability of Job Access are displayed in Table 5[19]:

[Table 5]

In this case it can be observed that both men and women are less likely to find jobs in the recession than in an expansionary period, though the drop in job access for men is almost twice as great as for women (15 pp vs. 8 pp.). This sharp drop in unemployment outs is explained in almost equal measures by compositional effects versus non-compositional (differences in coefficients) effects[20]. The contribution of compositional effects may be attributed to many covariates, but the most important ones are the following:

First and most important, the increase in unemployment duration of most unemployed workers accounts for around 33% of the compositional effects and 18%-19% of the raw

[19] Table A.5 presents the detailed estimation of the job finding probabilities for men and women and for expansion and recession respectively. Based on these estimations, we use the GU correction to identify the contribution of each category of dummy variables to explaining gender differences in differences in job access in recession compared to expansion.

[20] Using the conditional log-log function to estimate the unemployment hazard rate, the compositional effects are estimated to be -0.0465 for females and -0.0348 for males whereas the differences in coefficients are estimated to be -0.0798 and 0.0693, respectively

differential in the job finding probability in the recession compared to the expansionary period. As the recession continues, the share of short-term unemployed individuals in the pool of the unemployed gradually falls, as does the outflow rate from unemployment. As duration of unemployment increases, the probability of finding a job decreases. That is, unemployment exhibits negative state duration for job access. This might be due to depreciation of human capital skills, stigmatization of workers or lose of social networks. Thus, for any of these reasons, an increasing pool of long-term unemployed may generate hysteresis (Blanchard and Summers (1987)) and slow down future reductions in the unemployment rate. This composition effect is also found to be important in Bachmann and Sinning (2012) and in an earlier study by Baker (1992). Although neither of these studies explores gender differentials, both studies show that changes in the duration of unemployment seem to be a special feature of deep recessions. Interestingly, Bachmann and Sinning (2012) find that the composition of unemployment by duration is the most important determinant of the outflow rate in US and it explains 9% of the raw differential in unemployment outflows between booms and recessions. Note that the importance of the change in the composition of unemployment duration is much higher for Spain.

Second, the drop in aggregate demand, proxied by GDP growth, also explains the observed drop in the probability of finding a job. This indicates that the increasing difficulties in job access stem partially from the severe lack of aggregate demand. Interestingly, this effect differs by gender since for women it explains 23.6% of the compositional effects (13.4% of the raw differential in outflows) whereas for men it amounts to 40% (21.3% of the raw differential in outflows).

As it is also found in Elbsy et al (2013), the unemployment benefit system also plays a role within the compositional effects as it is the third biggest contributing factor in explaining the drop in the probability of job access. This accounts for 20% of the compositional effects for women and 12% for men. This is due to three main factors: UI benefit coverage and average length of benefit entitlement are both higher in recession versus expansion and the receipt of assistant benefits has increased. The first two factors are due to the fact that new entrants into unemployment during the recession, particularly in the early stages, had more labour market experience and tenure. There is ample evidence that receiving unemployment benefits delays job finding as a consequence of a decrease in search intensity[21] (recent evidence is provided in Rebollo-Sanz (2014) for Spain and Tatsiramos (2009) for Europe). The increase in the pool of unemployed workers with higher benefits in the recession contributes to the explanation of the drop observed in the job finding probability[22]. The third one is explained because the exhaustion of insurance benefits has been much more common in recession than in expansion due to the lack of job offers.

[21] See Tatsiramos and Van ours (2014) for a recent survey on the effects of unemployment insurance on the unemployment exit probability.

[22] Rebollo-Sanz (2012) and García-Pérez and Rebollo-Sanz (2014) find a strong positive relationship between the maximum duration of UI benefits and unemployment spell duration for Spain in the recent recession using the same dataset that we are using here.

Other minor changes in the composition of unemployment that lead to a drop in the probability of job access are the increased presence of immigrants, young and low educated workers and workers who previously held an indefinite contract within the pool of unemployed workers. This last result is due to the fact that liquidity constraints faced by workers with indefinite contracts are lower than those faced by fixed-term contract workers given that the former receive substantially higher severance payments when they are laid off. These results are highly interesting since they reject the hypothesis that unemployment duration increases in recession mainly due to the characteristics of the new mix of unemployed[23]. This result is in line with the one presented in Shimer (2012) who concludes that observable changes in the composition of the unemployed population explain little of the overall fluctuations in the job finding probability.

With respect to returns to the observed characteristics (non-compositional effects), the main determinant, common to men and women, that leads to a drop in the job finding probability is unemployment duration (34.4% for women and 43.4% for men). Moreover, a look at the detailed decomposition of the covariates that describe unemployment duration reveals that this result is driven by the group of short-term unemployed. This is so because the job finding probability of the short-term unemployed decreases dramatically in downturns relative to upturns, whereas the job finding probability for long-term unemployed hardly changes. This means that we cannot argue that the worsening of the negative state dependence is leading to hysteresis in Spain. But it is important to understand the sources of hysteresis when we combine it with the results presented for the composition effects. During the crisis, short-term unemployed workers have experience an important drop in the job finding probability increasing the pool of long term unemployment. Interestingly, Song and Von Watcher (2014) and Elsby et al. (2013) also find for US that the exit rates from long-term non-employment do not exhibit strong cyclical movement.

It is also remarkable to note that the contribution of unemployment benefits to the non-compositional effects is negative, i.e., does not contribute to explain the observed drop in the unemployment exit rate. This is because during the crisis, the disincentive effects or the moral hazard effect of benefits have dropped. In the recession context, workers face higher uncertainty about the chances of receiving a job offer in the near future and they are more eager to accept a job offer even if unemployment benefits are not yet exhausted. Hence, our results do not support the principle that the unemployment benefit system should be particularly important to explain the large drop in the job finding probability[24].

Other minor determinants also common to women and men are mainly related to individual characteristics such as being an immigrant and education level (basically low

[23] That is, if groups than can typically expect relatively longer durations enter unemployment in proportionately greater number during a recession, the aggregate average unemployment duration will increase, though average unemployment duration at the individual level will remain hardly the same. As Baker (1982) does, we obtain that the variation in the composition of entrants is insufficient to drive the variation observed in aggregate unemployment duration.

[24] This is in line with the recent research that suggests only modest impacts of UI extensions on the search effort and duration of unemployment of unemployment insurance recipients (Schmieder, Von Wachter, and Bender 2012). Much of the impact of unemployment insurance on job search comes from reducing liquidity constraints than traditional job search disincentives.

educated and young workers and immigrants find it harder to exit unemployment). As for the case of unemployment ins, it emerges that some differences in coefficients, mainly related to the sector of activity -in particular to construction- and job qualification and education –in particular low skill and educated workers-, help explain the drop in the job finding for men but not for women, and hence lead to the observed convergence in job finding rates.

In view of these results, our findings about gender differentials in unemployment outs in the downturn with respect to the previous upturn can be summed up as follows:

First, job finding probabilities are lower in the recession than in the expansionary period for both men and women but more so for men. Indeed, the probability of finding a job has decreased by around 15 pp. for men and 8 pp. for women. This different effect of coefficients has led to convergence in job access rates by gender.

Second, among the determinants of this drop, we find that negative state dependence, lack of demand and institutional unemployment features such as unemployment benefits are the main sources of such a drop for both men and women. Furthermore, the decline in unemployment outs has been accompanied by a record rise in long-term unemployment. This has resulted in a persistent residue of long-term unemployed persons with relatively weak search effectiveness, depressing the strength of a potential upcoming recovery. Moreover, there is a substantial gender differences in the role played by state dependence in the drop in job access rates, which is larger for men than for women.

Finally, the drop in the job access rate for people formerly employed in construction has been much greater for men than for women. Indeed, the different role played by state dependence together with the drop in job access for people previously employed in construction have been the main drivers for the convergence in job access rates by gender in the recent downturn compared to the previous upturn.

8. Unemployment dynamics and gender differentials in the upcoming recovery: Counterfactual analysis

So far we have shown that unemployment rates have increased to unprecedented levels during the current downturn and that this trend is closely related to the spectacular drop in unemployment outs. This has resulted in a persistent increase in the fraction of long-term unemployed workers, whose weak search effectiveness may generate hysteresis (Blanchard and Summers (1987)).

Indeed, there is a growing body of recent literature that considers a range of possible sources of hysteresis in the US Great Recession, such as sectoral mismatching, extension of unemployment insurance, negative state dependence and an increasing proportion of long-term unemployed (see Shimer (2012), Lazear and Spletzer (2012), Elsby et al (2010) among others). These authors find no clear evidence of unemployment outs being led by these structural sources[25]. Particularly, in relation to the increase in the proportion of long-term

[25] They use a very different approach from the one taken in this paper. Particularly, they do not work with individual data and they follow a time series approach.

unemployed, Elsby et al (2009) argue that long-term unemployment is unlikely to lead to the degree of hysteresis seen in Europe since the 1980s. However, more recently, Barnichon and Figura (2014) find that, in contrast to the recession of the early 80s, a large increase in the proportion of long-term unemployed has driven down aggregate matching efficiency to exceptionally low levels, leading to a breakdown of the standard matching function in the US and preventing unemployment from going down faster and participation from going up.

In any case, persistence of unemployment is far more significant in European countries, especially in some of them, such as Spain, where long-term unemployment has reached the unprecedented figure of 66% of all unemployed workers. Indeed, Hobijn (2012) finds rightward shifts in the Beveridge Curve of many European countries such as Portugal, Spain, Sweden and the UK, which suggests that sectoral mismatching may be an issue for recovery in these countries. Furthermore, they find that Spain has experienced a 50% decline in matching efficiency in the Great Recession, which is indicative of very substantial deterioration in its working situation.

From our analysis of the decomposition of unemployment outs we have learnt that there might be a sectoral mismatch, as layoff rates are higher for workers in the construction sector and workers previously employed in construction face greater difficulties in finding another job. Indeed, if this sector faces a structural decline in the upcoming recovery, sectoral mismatching might be an issue as (male) workers formerly employed in the construction sector would need to be relocated to other sectors. They may face difficulties in acquiring the training and education required for the new jobs available in the growing (primarily service) sectors. We also present some evidence that rules out the idea that the unemployment benefit system might be important in causing hysteresis. In any case, these two effects have been less important than the effect of the large proportion of long-term unemployed.

It is beyond the scope of this paper to determine whether the changes observed in the unemployment rate and in the gender gaps in unemployment rates are purely cyclical or structural. Nevertheless, we would like to explore whether it might be difficult for the unemployment rate to drop to pre-recession levels even in the context of an upcoming expansionary cycle. To that end we propose to use our predicted unemployment outs in the upturn and in the downturn and use different scenarios to simulate the speed at which jobs will be found in the upcoming recovery and which type of workers will benefit more and less from that recovery.

Prospects for the labour market – Some counterfactuals for the probability of finding a job

Our specific purpose is to illustrate the potential importance of the compositional aspect for job access in the context of an eventual recovery. Hence, we propose an exercise that consists of using parameter estimates from expansion and recession to simulate the dynamics of a pool of unemployed workers under alternative scenarios. We are aware that our reduced duration model cannot offer an answer in terms of causal evaluation but we believe that it is still interesting to perform it to get an insight into the dynamics of the pool of unemployed workers at the onset of the economic recovery.

More specifically, we simulate hazard rates from unemployment for 12 consecutive quarters under the following five scenarios:

1. Scenario 1 (expansionary pre-recession context): we take the characteristics of the pool of unemployed workers in 2007 and parameter estimates corresponding to a model estimated using the period 2000-2007.
2. Scenario 2 (expansionary pre-housing boom context): we take the characteristics of the pool of unemployed workers in 2003 and parameter estimates corresponding to a model estimated using the period 2000-2003. This scenario enables us to simulate the hazard rates from unemployment in an expansionary context without the specific features of the final stage of the housing boom.
3. Scenario 3 (recession context): we take the characteristics of the pool of unemployed workers in 2013 (the most recent pool of unemployed workers on which we have information using the CWLS) and parameter estimates corresponding to a model estimated using the recession period (2008-2013). This scenario simulates the intensity of unemployment outs for the current pool of unemployed. For GDP growth, we attribute the quarterly GDP growth which is observed/expected for the 12 quarters corresponding to the years 2014-2016.[26]
4. Scenario 4 (counterfactual 1): we take the characteristics of the pool of unemployed workers in 2013 (the most recent pool of unemployed workers on which we have information) and parameter estimates corresponding to a model estimated using the previous expansionary period (2000-2007). With this scenario our aim is to illustrate the hazard rates of the current sample of unemployed workers but in an expansionary context such as the pre-recession one. As before, quarterly GDP growth is that which is observed/expected for the years 2014-2016.
5. Scenario 5 (counterfactual 2): we take the sample of unemployed workers in 2013 and parameter estimates corresponding to a model estimated using the pre-housing boom period – 2000-2003. We exclude the final years of the housing boom (2004-2007) because the upcoming recovery is highly unlikely to resemble that context. As before, quarterly GDP growth is that which is observed/expected for the years 2014-2016.

Each worker's unemployment spell is simulated 1000 times over a 12-quarter period. From each simulation we can construct individual unemployment dynamics, which are then used to compute survival probability rates in each quarter (Figure 7). For the latter simulation, time varying covariates are properly updated (i.e. age and the variables related to the UIB system). In addition, this exercise can also be executed for certain types of individual, in particular for individuals with different unemployment durations at the time when the simulation starts. We divide the pool of unemployed workers into four groups: (i) unemployed for 1-6 months; (ii) unemployed for 7-12 months; (iii) unemployed for 13-24 months; and (iv) unemployed for 25-36 months. The panels of Figure 8 represent survival rates in

[26] Using the information provided by the European Commission, the OECD and the FMI, annual expected growth in GDP for 2015 varies between 2.6% and 3%. For 2016 the official forecasts are very similar. Hence in our simulations, we use a quarterly GDP growth of 0.8%, i.e. an optimistic scenario.

unemployment for each group of unemployed workers for a 12-quarter (3-year) interval and for the five different scenarios described above.

Figure 7 reveals the following issues[27]:

- First, as expected, survival rates in unemployment strongly depend on whether the context is expansionary or recessionary, and this dependence is notably stronger for unemployed men than for the corresponding women. In an expansionary period such as the one Spain enjoyed in 2000-2007, after 4 quarters (1 year) around 52% (42%) of women (men) would remain unemployed. But in a context of recession these survival rates would increase to 68% for women and 65% for men.
- Second, the two counterfactual exercises illustrate that even in an expansionary context such as the ones that Spain underwent before 2007, the characteristics of the pool of unemployed workers in 2013 would delay unemployment outs to a great extent. This is so for both men and women. The estimated survival rates in the two counterfactual contexts closely resemble the patterns observed in the recent recession context rather than in the former expansionary one, even though the parameters attributed correspond to an expansionary period.

To examine the second result in more depth we illustrate survival rates in the different scenarios for workers with different unemployment durations. The first two panels of Figure 8 represent estimated survival rates for workers with short unemployment durations (<6 months, and 7-12 months), whereas the last two represent estimated survival rates for the long-term unemployed (1-2 years, 2-3 years). The following issues are worth noting:

- First and most importantly, the survival rates of long term unemployed workers are much higher than those estimated for the pool of short-term unemployed: around 60% of the long-term male and female unemployed workers would still remain unemployed in a 2-year span. Furthermore, estimated survival rates for the group of LTU do not depend much on the context (expansionary/recessionary), but rather stay very high independently of the sign of the business cycle.
- Second, survival rates for the group of short-term unemployed, and in particular for men, are more affected by the economic context (expansion/recession) than those observed for the LTU. Indeed, survival rates for short-term male unemployed workers in the two counterfactual exercises are closer to those estimated for the expansionary periods than for the recession years. The explanation for this is that for short-term unemployed workers state dependence is not a major barrier to job access. The fact that this is particularly so for men rather than women is because, as shown in the previous section, the impact of

[27] It can be checked how far the Spanish scenario by the end of 2014 (which is already known) resembles any of those depicted in Figure 7: average quarterly flows of Spanish workers from unemployment to employment in 2014 amounted to 20% for men and 18% for women (see http://www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736176907&menu=resultados&idp=1254735976595). From our simulated model we find that the job-finding probability in the first year, i.e. 2014, is likely also to be around 18.5% for men and 19% for women.

economic activity is much stronger for men than for the corresponding women. Notwithstanding this, unemployment outflows for women are clearly higher for the short-term unemployed than for the long-term unemployed, although the economic context is not as significant as for men.

These results lead us to conclude that in any upcoming recovery unemployment outs will particularly affect short-term male unemployed workers. Long-term unemployed individuals will face enormous difficulties in accessing jobs, in both upturn and downturn contexts. This may be because of sectoral mismatching, weaker job search effectiveness among this group of workers, depreciation of their human capital, etc. Given that at present 64% of all unemployed workers are long-term unemployed, the rate of unemployment is expected to remain high for many years, even in a strong recovery framework. Implementation of successful, active policies directed at retraining and relocating LTU workers are, however, expected to alleviate this problem.

9. Summary and Conclusions

The 2007 recession has had a disproportionately negative effect on working men compared to working women. As Sahin et al (2010) report, from the start of the recession in December 2007 to January 2010, payroll employment in the USA decreased by 8.2% for men and by only 3.7% for women. In Europe, Spain is second only to Greece as the country where the recent recession has destroyed most jobs: 3.8 million, around 18% of the whole workforce. However, 25% of all jobs done by men have been lost during the recession compared to only 10% of those done by women.

Although information on aggregate employment destruction is necessary, is not sufficient in itself to account for labour market outcomes for men and women. Gender differences in gross labour market flows from unemployment to employment (unemployment outs) and from employment to unemployment (unemployment ins) help identify gender differences in the mechanisms that underlie job losses and job access. This paper compares gender differences in the behaviour of unemployment ins and outs in Spain in the Great Recession with the previous upturn.

This is done by using a longitudinal database extracted from Social Security Records (CWLS) from 2000 to 2013 which offers detailed information on all employment and unemployment records for individuals throughout their labour market trajectories.

Our results confirm the following:

Overall, unemployment ins have remained barely constant for females but rather have increased in around 1.5 pp for males. This different behaviour has led to a convergence in layoff rates by gender. To understand the underlying process, it must be noted that the current crisis has led to a substantial change in the composition of employment: Workers who kept their jobs during the recession are those with higher human capital and more stable jobs. This positive selection process has been stronger for females than for males, which explains a (small) fraction of the observed convergence in layoff rates mentioned before. Second, job characteristics, such as temporary contracts, working in the public sector, and other individual characteristics such as low tenure and low educated workers lead to a higher layoff risk during the downturn than during the upturn. This effect is stronger for men than for women. In addition, the end of the housing boom, which has led to a sizable number of layoffs, has hit male employment disproportionately. These are in fact the main drivers in explaining the decrease in gender differentials in layoff rates.

With respect to unemployment outs, we document a huge drop in job access rates in recession as compared to expansion: the probability of finding a job has decreased by around 15 pp. for men and 8 pp. for women. This different behaviour explains the observed convergence in job access rates by gender in the last years. Among the determinants of this drop, we find that negative state dependence, lack of demand, institutional unemployment features such as unemployment benefits and the sector of activity in the former job, are the main sources of such a drop for both men and women but more so for men. Furthermore, the decline in unemployment outs has been accompanied by a record rise in long-term unemployment. This is likely to result in a persistent residue of long-term unemployed persons with relatively weak search effectiveness, depressing the strength of the recovery. The different role played by state dependence together with the drop in job access for people previously employed in construction have been the main drivers for the convergence in job access rates by gender in the recent downturn compared to the previous upturn.

Our simulations show that in any upcoming recovery unemployment outs will affect particularly short-term (male) unemployed workers, as males respond more to cyclical forces than women. Long-term unemployed individuals will face enormous difficulties to access a job even in an expansionary context, as their job access difficulties remain very high in upturn and downturn contexts. Given that at present 64% of all unemployed workers are long-term unemployed, the rate of unemployment is expected to remain high for many years, even in a strong recovery framework. Implementation of successful, active policies directed at retraining and relocating LTU workers are, however, expected to alleviate this problem.

Hence, the bottom line is that the Spanish economy, as other European countries, faces two major jobs challenges. The first is the need for strong economic recovery to increase vacancy creation, hiring, and create a sustained jobs expansion. The second is the need for policies to address structural labor market problems to improve the matching of job seekers to new job openings and to assist in the labor market adjustments of the long-term unemployed.

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Figures and Tables

Figure 1

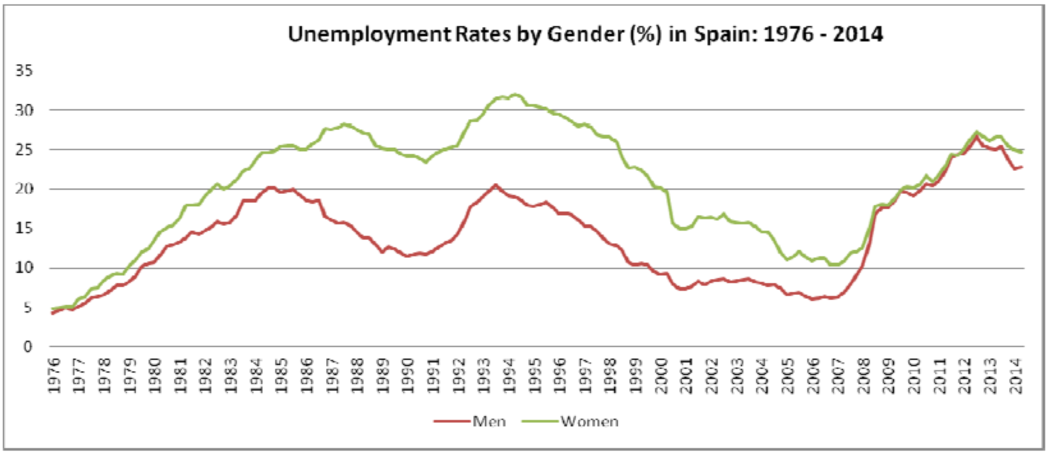


Figure 2

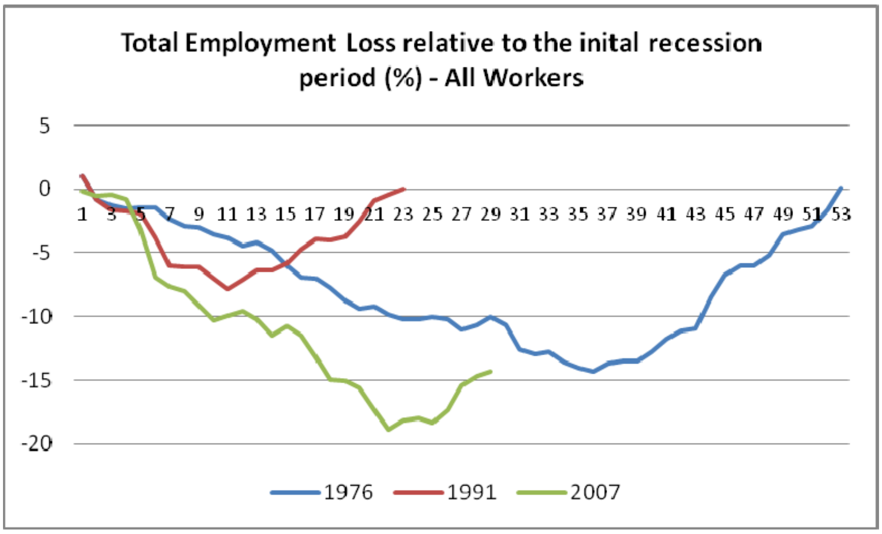
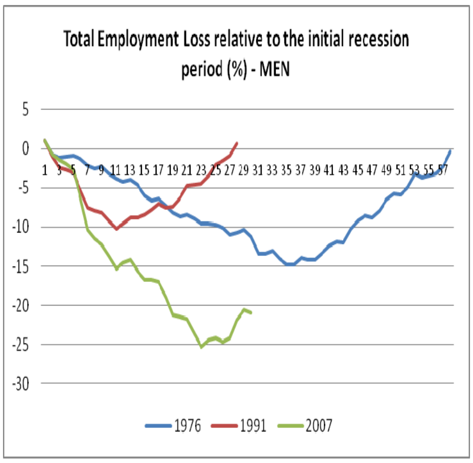


Figure 3A

Figure 3B



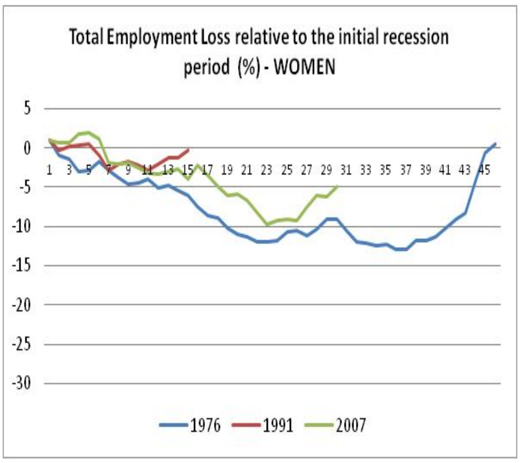


Figure 4: Annual Averages of quarterly Unemployment Inflows
by gender and contract type

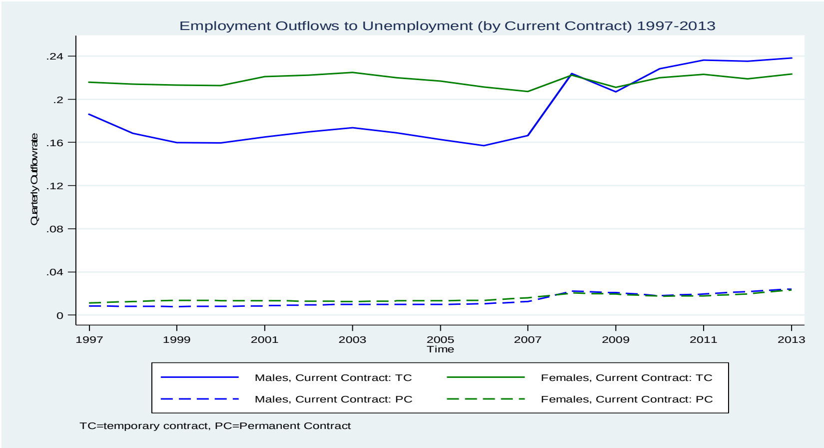


Figure 5: Annual Average of Quarterly Unemployment Outs (by Gender and Type of Contract)

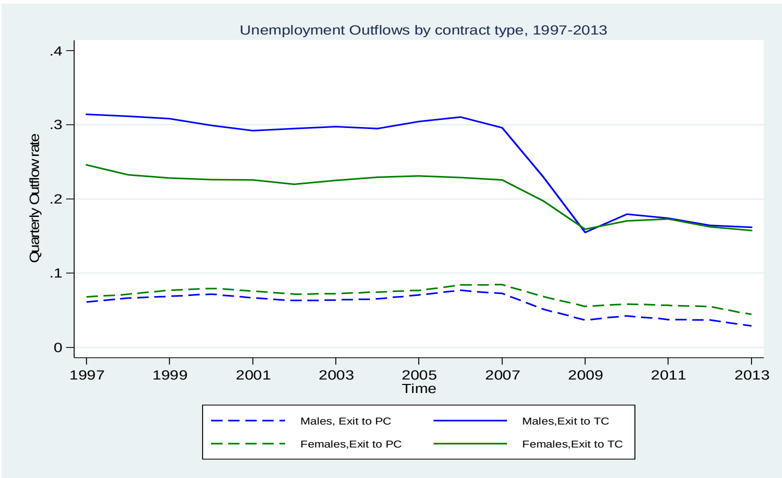


Figure 6: Change in ins and outs of unemployment during the crisis

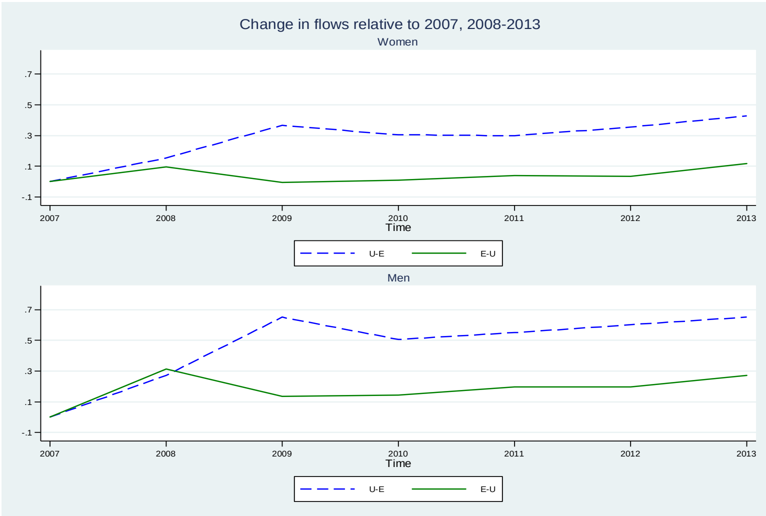


Figure 7: Unemployment Survival Rates along 12 quarters – All Unemployed Workers in the Sample

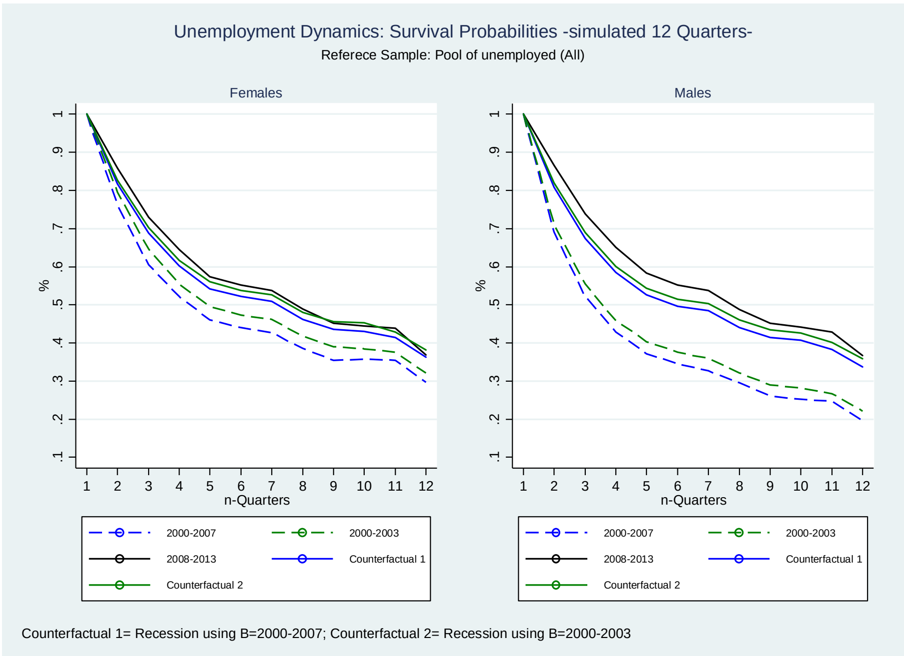
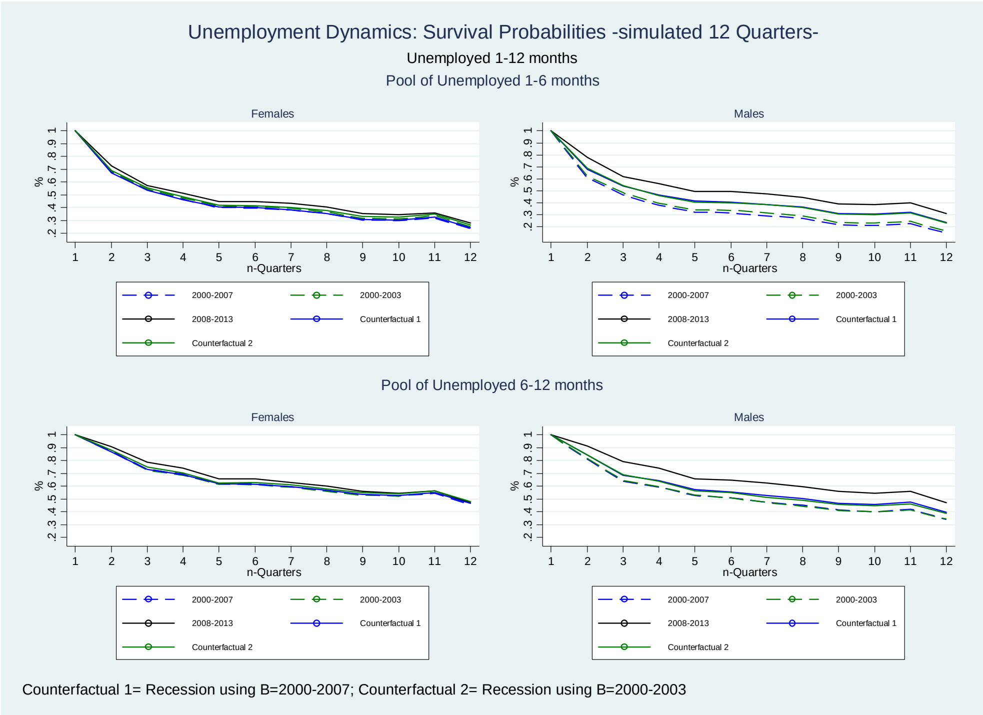


Figure 8: Estimated Unemployment Survival Rates by Duration of Unemployment

Panel a: Short-term



Panel b: Long-Term

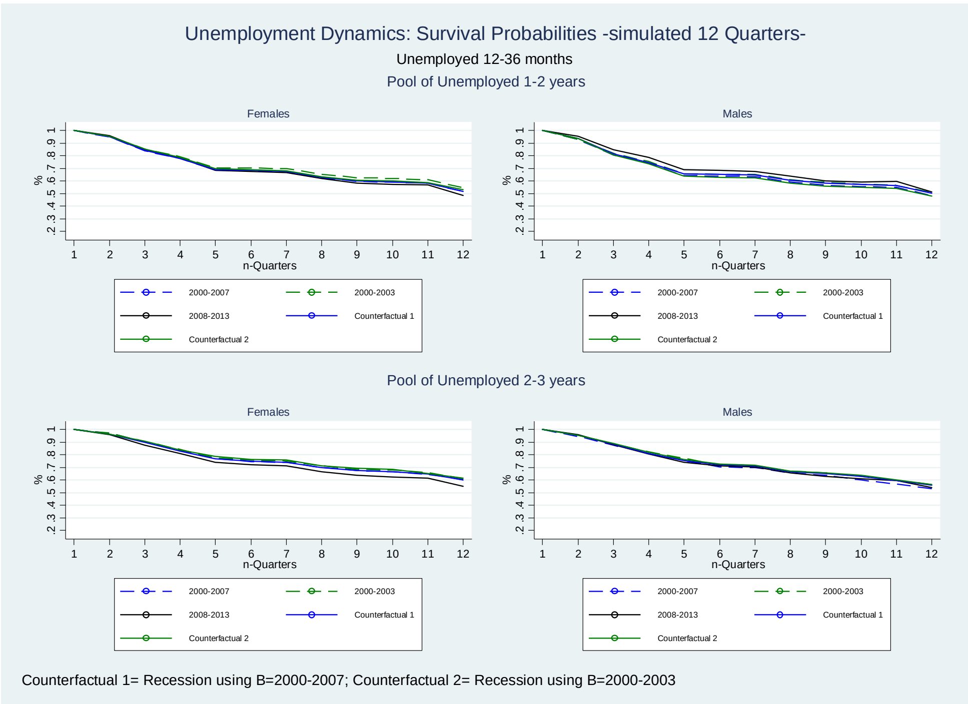


Table 1: Distribution of job spells by gender (Time Unit: Quarter)

		2000-2007		2008-2013	
		Females	**Males**	**Females**	**Males**
Age	<30	29%	27%	20%	18%
	30-45	47%	45%	50%	50%
	>45	22%	28%	30%	31%
Experience		37	46	38	44
Tenure	1-3 months	13%	12%	10%	9%
	4-6 months	16%	14%	13%	11%
	6-12 months	18%	17%	16%	15%
	12-24 months	8%	8%	9%	8%
	24-36 months	11%	11%	13%	12%
	36-60 months	15%	16%	19%	19%
	>60 months	15%	19%	17%	22%
Contract	Full-time TC	31%	29%	26%	24%
Types	Full-time PC	69%	70%	73%	75%
	Part-time	21%	5%	27%	9%
Temporary Help Agency		1.3%	1.2%	0.7%	1%
Sectors*	Agr	0.2%	0.1%	0.4%	0.5%
	Ind	11%	24%	8%	21%
	Constr.	2%	16%	2%	12%
	Commerce+Hotels	26%	19%	27%	22%
	Transport+Commu+Rent	4%	7%	3%	8%
	Financial Servs	3%	3%	3%	3%
	Construction Servs	1%	1%	0.8%	0.6%
	Serv+Computers+Tech. Servs	15%	10%	16%	12%
	Education+Health+Culture	22%	7%	25%	9%
	Other Services	12%	8%	12%	8%
Firm-Size	<10	42%	48%	26%	29%
	>10<50	9%	11%	13%	16%
	50-100	7%	8%	10%	11%
	>100	%	%	%	%
Education	Less than Primary	10%	18%	9%	14%
	Less than Secondary	30%	36%	29%	35%
	Secondary	34%	29%	32%	30%
	University	24%	15%	28%	19%
Job Cualification	High Skill	18%	14%	20%	16%
	Medium Skills	30%	25%	30%	26%
	Low Skills	51%	60%	48%	56%

Note: PC=Permanent Contract;TC=Temporary Contract; High Skills: Technical engineers, experts and qualified assistants; Administrative and Workshop Managers; Technical engineers, experts and qualified assistants. Medium Skills: non-qualified assistants; Administrative Officer; junior staff; Administrative Assistants. Low Skills: First and second class officials; Third order officials; maintenance and handymen. * We restrict to the general regime.

Table 2: **Quarterly Layoff Rates by sample characteristics - Females versus Males and Expansion versus Recession**

		2000-2007			2008-2013		
		% of Females	**Layoff Rate Males**	**Females**	**% of Females**	**Layoff Rate Males**	**Females**
Total		45%	**5.5%**	7.4%	45%	7.2%	**7.5%**
Age	<30	46%	10%	12%	50%	14%	14%
	30-45	46%	4.2%	6.0%	49%	6.5%	6.7%
	>45	38%	2.8%	4.3%	47%	4.1%	4.5%
Contract Types	TC	43%	16%	21%	50%	22%	22%
	PC	44%	0.9%	1.3%	48%	2.0%	1.9%
Part-time		75%	12%	10%	75%	13%	10%
Public Firm		49%	10%	10%	49%	19%	14%
Sectors	Agr	28%	7.8%	10.1%	27%	15%	14%
	Ind	26%	3.7%	7.7%	27%	4.5%	6.6%
	Construction	10%	**9.5%**	**5.9%**	13%	**15%**	**7.8%**
	Commerce+ Hotels	51%	5.6%	9.4%	54%	7.4%	9.6%
	Transport+ Communications	29%	**3.7%**	6.1%	31%	5.5%	6.5%
	Financial Servs	43%	0.8%	1.7%	51%	1.3%	1.7%
	Construction Servs	55%	9.3%	9.7%	56%	7.8%	6.5%
	Rent Serv.+ Computers+ Tech. Servs	55%	7.4%	8.7%	54%	7.6%	8.0%
	Education+Healt+Culture	70%	6.6%	5.9%	72%	6.2%	6.3%
	Other Services	53%	5.9%	5.8%	57%	4.9%	6.5%
Firm-Size	<10	41%	8.8%	8.6%	46%	**11%**	9.8%
	>10<50	39%	6.2%	7.2%	44%	6.8%	7.4%
	50-100	41%	5.8%	7.4%	45%	5.9%	7.2%
	>100	49%	4.6%	6.2%	53%	4.6%	6.2%
Education	Less than Primary	30%	7.4%	9.9%	37%	11%	11%
	Less than Secondary	39%	6.2%	8.9%	44%	8.7%	9.2%
	Secondary	48%	4.2%	**6.1%**	50%	5.2%	**6.3%**
	University	56%	4.1%	6.3%	59%	3.9%	5.6%
Job Cualification	High Skill	50%	1.8%	3.8%	54%	2.5%	4.3%
	Medium Skills	48%	2.5%	4.2%	52%	3.9%	4.9%
	Low Skills	40%	**7.7%**	10.6%	44%	**10%**	10%

Note: PC=Permanent Contract;TC=Temporary Contract

High Skills: Technical engineers, experts and qualified assistants; Administrative and Workshop Managers; Technical engineers, experts and qualified assistants. Medium Skills: non-qualified assistants; Administrative Officer; junior staff; Administrative Assistants. Low Skills: First and second class officials; Third order officials; maintenance and handymen.

Table 3: Decomposition of the Estimation of the Layoff probability by gender – LPM (Recession versus Expansion: 2000-2013)

	Women		Men		DD (Women-Men)	
Unconditional Difference	**0.00045**		**0.0149**		**-0.0158**	
	Absolute Contribution	Relative Contribution	Absolute Contribution	Relative Contribution	Absolute Contribution	Relative Contribution
Composition Effect						
Total	***-0.0214***	***-4697%***	***-0.0184***	***-111.2%***	***-0.0030***	***18.7%***
Education	-0.0004	1.65%	-0.0007	3.66%	0.0003	-10.7%
Age	0.0010	-4.59%	0.0009	-4.77%	0.0001	-3.4%
Experience	-0.0015	7.00%	0.0008	-4.46%	-0.0023	77.2%
Inmigrant	-0.0010	4.66%	-0.0013	7.10%	0.0003	-10.3%
Children	-0.0001	0.38%	0.0002	-1.24%	-0.0003	10.3%
Recall[28]	0.0001	-0.63%	-0.0001	0.37%	0.0002	-6.7%
Job Cualification	-0.0008	3.70%	-0.0009	4.98%	0.0001	-4.2%
Sector	-0.0011	5.13%	-0.0018	9.82%	0.0007	-23.6%
Public Firm	-0.0021	9.66%	-0.0011	6.14%	-0.0009	31.2%
Contract Types	-0.0044	20.52%	-0.0066	36.05%	0.0022	-74.6%
Firm Size	-0.0035	16.12%	-0.0050	27.20%	0.0016	-51.8%
GDP Growth (quarterly)	-0.0009	4.40%	0.0037	-20.31%	-0.0047	155.8%
Tenure	-0.0069	32.00%	-0.0065	35.46%	-0.0003	10.8%
Differences in Coefficients						
Total	***0.0218***	***4797%***	***0.0349***	***211.2%***	***-0.0131***	***81.3%***
Education	-0.0007	-3.31%	0.0013	3.6%	-0.0020	15.6%
Age	-0.0002	-0.88%	-0.0001	0.2%	-0.0001	1.0%
Experience	0.0002	0.83%	-0.0045	-8.1%	0.0047	-36.0%
Inmigrant	0.0001	0.28%	0.0001	1.0%	0.0000	-0.1%
Children	-0.0017	-7.56%	0.0007	1.5%	-0.0024	18.3%
Recall	-0.0018	-8.28%	0.0005	1.2%	-0.0023	17.4%
Job Cualification	-0.0005	-2.35%	0.0009	3.4%	-0.0014	11.0%
Sector	-0.0049	-22.43%	0.0042	14.7%	-0.0091	69.8%
Public Firm	0.0063	28.57%	0.0068	18.7%	-0.0005	3.8%
Contract Types	0.0002	1.14%	0.0006	8.3%	-0.0003	2.5%
Firm Size	0.0015	7.05%	0.0043	11.8%	-0.0027	20.9%
GDP Growth (quarterly)	0.0094	43.01%	0.0059	30.9%	0.0035	-26.5%
Tenure	0.0008	3.60%	-0.0006	-1.9%	0.0014	-10.8%
Constant	0.0132	60.34%	0.0149	14.5%	-0.0017	13.2%

[28] This covariate is a dummy variable that takes value one when the worker had been recalled and zero otherwise. This variable is relevant for a gender analysis since women tend to had more temporary layoffs than men.

Table 4: Unemployment Exit Rates –
Separately by Gender and by Period (recession/expansion)

		2000-2007		2008-2013	
		Males	**Females**	**Males**	**Females**
Total		**36%**	31%	21%	**23%**
Age	<30	40%	35%	25%	27%
	30-45	41%	29%	23%	22%
	>45	20%	23%	13%	17%
TC		40%	33%	24%	26%
PC		21%	21%	14%	13%
Part-time		32%	30%	22%	23%
Temporary Help Agency		50%	46%	35%	34%
Public Firm		34%	30%	21%	22%
Sectors	Agr	35%	28%	25%	23%
	Ind	33%	29%	18%	18%
	Constr.	**44%**	**24%**	**21%**	**13%**
	Commerce+ Hotels	34%	30%	22%	22%
	Transport+ Communications	**33%**	33%	**22%**	24%
	Financial Servs	19%	28%	13%	18%
	Construction Servs	30%	25%	10%	10%
	Rent Serv.+ Computers+ Tech. Servs	39%	33%	23%	22%
	Education+Health+ Culture	36%	37%	28%	31%
	Public. Admon.+Other Services	28%	27%	18%	21%
Firm-Size	<10	37%	29%	**20%**	19%
	>10<50	36%	30%	21%	22%
	50-100	36%	31%	22%	24%
	>100	34%	36%	22%	28%
Education	Less than Primary	35%	26%	23%	19%
	Less than Secondary	41%	30%	18%	22%
	Secondary	35%	32%	23%	23%
	University	30%	34%	22%	27%
Job Cualification	High Skill	28%	38%	20%	28%
	Medium Skills	29%	30%	20%	22%
	Low Skill	**38%**	30%	**22%**	22%

Table 5: Decomposition of the Estimation of the Job Finding probability by gender – LPM (Recession versus Expansion)

	Women		Men		DD (Women-Men)	
Unconditional Difference	**-0.0813**		**-0.1499**		**0.0686**	
	Absolute Contribution	Relative Contribution	Absolute Contribution	Relative Contribution	Absolute Contribution	Relative Contribution
Composition Effect						
Total	***-0.0465***	***57.2%***	***-0.0799***	***53.3%***	***0.0334***	***48.7%***
Education	-0.0004	0.8%	-0.0009	1.1%	0.0005	1.5%
Age	-0.0036	7.7%	-0.0013	1.6%	-0.0023	-6.8%
Experience	0.0008	-1.6%	0.0016	-1.9%	-0.0008	-2.3%
Immigrant	-0.0027	5.9%	-0.0029	3.7%	0.0002	0.7%
Recalls	-0.0002	0.3%	0.0005	-0.6%	-0.0006	-1.8%
Job Qualification	0.0006	-1.4%	0.0018	-2.2%	-0.0011	-3.4%
Sector	0.0010	-2.1%	0.0006	-0.7%	0.0004	1.2%
Public Firm	-0.0012	2.5%	-0.0019	2.4%	0.0008	2.2%
Contract Types	-0.0068	14.5%	-0.0072	9.1%	0.0004	1.4%
Firm Size	0.0018	-3.9%	-0.0007	0.9%	0.0025	7.6%
GDP Growth **(quarterly)**	-0.0110	23.6%	-0.0319	40.0%	0.0210	62.9%
UB Benefits	-0.0095	20.4%	-0.0102	12.8%	0.0007	2.1%
Unemp. Length	-0.0155	33.3%	-0.0271	33.9%	0.0116	34.8%
Differences in Coefficients						
Total	***-0.0348***	***42.8%***	***-0.0700***	***46.7%***	***0.0352***	***51.3%***
Education	-0.0016	4.6%	-0.0095	13.6%	0.0079	22.5%
Age	-0.0009	2.6%	-0.0039	5.6%	0.0030	8.6%
Experience	0.0033	-9.5%	0.0008	-1.2%	0.0025	7.1%
Immigrant	-0.0032	9.2%	-0.0079	11.4%	0.0048	13.5%
Recalls	-0.0027	7.8%	0.0010	-1.5%	-0.0037	-10.6%
Job Qualification	0.0076	-22.0%	0.0047	-6.7%	0.0029	8.4%
Sector	0.0022	-6.2%	-0.0089	12.7%	0.0111	31.5%
Public Firm	-0.0060	17.2%	-0.0047	6.7%	-0.0013	-3.7%
Contract Types	-0.0015	4.3%	0.0001	-0.1%	-0.0016	-4.6%
Firm Size	0.0001	-0.4%	-0.0001	0.1%	0.0003	0.7%
GDP Growth (quarterly)	0.0077	-22.1%	0.0153	-21.9%	-0.0076	-21.7%
UB Benefits	0.0114	-32.6%	0.0102	-14.6%	0.0011	3.2%
Unemp. Length	-0.0120	34.4%	-0.0304	43.4%	0.0184	52.3%
Constant	-0.0392	7.8%	-0.0366	-1.5%	-0.0037	-10.6%

Annex Tables:

Table A.1: Estimates of the layoff probability – LPM
Separately by Gender and by Period (recession/expansion)

	2000-2007		2008-2013	
	Females	Males	Females	Males
Less than Secondary Education	-0.0038**	-0.0052**	-0.0041**	-0.0062**
Less than University Education	-0.0110**	-0.0051**	-0.0136**	-0.0127**
University Education	-0.0098**	-0.0016**	-0.0182**	-0.0166**
Age, <30	-0.0357**	-0.0319**	-0.0210**	-0.0275**
Age, 30-45	-0.0248**	-0.0228**	-0.0149**	-0.0174**
Experience	-0.0004**	-0.0002**	-0.0003**	-0.0002**
Inmigrant	-0.0479**	-0.0353**	-0.0430**	-0.0296**
Children of any age	0.0066**	0.0017**	0.0040**	0.0029**
Repeat Firm	0.0330**	0.0271**	0.0228**	0.0280**
High Skill:engineering, Judge and so on	-0.0503**	-0.0474**	-0.0494**	-0.0455**
High Skills: Technical engineers, experts and qualified assistants.	-0.0409**	-0.0407**	-0.0367**	-0.0357**
High Skills: Administrative and Workshop Managers	-0.0225**	-0.0280**	-0.0191**	-0.0248**
Medium Skills: non-qualified assistants.	-0.0140**	-0.0252**	-0.0079**	-0.0238**
Medium Skills: Administrative Officer	-0.0223**	-0.0305**	-0.0219**	-0.0295**
Medium Skills: junior staff	-0.0106**	-0.0179**	-0.0118**	-0.0176**
Medium Skills:Administrative Assistants	-0.0205**	-0.0202**	-0.0230**	-0.0268**
Low Skills: First and second class officials	-0.0033**	-0.0243**	-0.0008	-0.0173**
Low Skills: Third order officials	0.0003	-0.0167**	-0.0019*	-0.0140**
Firm Size:<5 employees	0.0124**	0.0082**	0.0304**	0.0287**
Firm Size:5-20 employees	0.0125**	0.0049**	0.0196**	0.0117**
Firm Size:20-50 employees	0.0148**	0.0053**	0.0202**	0.0102**
Public Firm	0.0293**	0.0458**	0.0749**	0.0980**
Tempary help agency	0.0878**	0.1182**	0.1223**	0.1284**
Contract Type: Part-time	0.0028**	0.0218**	0.0054**	0.0133**
Contract Type: Permanent	-0.1169**	-0.0952**	-0.0979**	-0.1025**
Contract Type:Intermittent PC	0.0218**	0.0423**	0.0095**	0.0058*
Contract Type:Employment Promotion PC	-0.1260**	-0.0943**	-0.0943**	-0.0933**
GDP growth rate	-0.0076**	-0.0063**	-0.0053**	-0.0086**
Tenure:1-3 m.	0.1518**	0.1208**	0.1525**	0.1472**
Tenure:4-6 m.	0.1302**	0.0951**	0.1336**	0.1112**
Tenure:7-12 m.	0.0774**	0.0542**	0.0732**	0.0512**
Tenure:13-24 m.	0.0481**	0.0362**	0.0377**	0.0275**
Tenure:25-36 m.	0.0454**	0.0332**	0.0351**	0.0246**
Tenure:36-60 m.	0.0353**	0.0270**	0.0259**	0.0195**
Constant	0.1408**	0.1256**	0.1232**	0.1323**

Note:Reference Group: Low skill/educated worker aged above 45 working in a big firm in the industry with a temporary contract. 14 sectoral indicators also included although not reported.
Statistical Significance: ** 95%, * 90%

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Table A.2: Job finding probability (LPM)
Separately by Gender and By Period (recession/expansion)

	2000-2007		2008-2013	
	Females	Males	Females	Males
Less than Secondary Education	0.0176**	0.0170**	0.0233**	0.0212**
Less than University Education	0.0123**	-0.0201**	0.0237**	0.0197**
University Education	-0.0081**	-0.0558**	0.0331**	0.0284**
Age, <30	0.0593**	0.0958**	0.0603**	0.0716**
Age, 30-45	0.0422**	0.0978**	0.0342**	0.0552**
Labor Market Experience	0.0001**	0.0002**	0.0000*	0.0001**
Inmigrant	0.0431**	0.0675**	-0.0414**	-0.0254**
Having job interruptions with the same firm	0.0460**	0.0254**	0.0297**	0.0217**
High Skill:engineers, Judges and so on	0.0289**	0.0069*	-0.0237**	-0.0183**
High Skills: Technical engineers, experts and qualified assistants.	0.0510**	0.0370**	0.0118**	0.0095**
High Skills: Administrative and Workshop Managers	0.0447**	0.0403**	0.0186**	0.0310**
Medium Skills: non-qualified assistants.	0.0300**	0.0273**	0.0184**	0.0177**
Medium Skills: Administrative Officer	0.0372**	0.0312**	0.0204**	0.0294**
Medium Skills: junior staff	0.0245**	0.0178**	0.0154**	0.0206**
Low Skills: Administrative Assistants	0.0326**	0.0088**	0.0147**	0.0180**
Low Skills: First and second class officials	0.0264**	0.0369**	0.0203**	0.0337**
Low Skills: Thrid class officials	0.0224**	0.0177**	0.0130**	0.0175**
Firm Size: < 5 employees	-0.0159**	0.0046**	-0.0102**	0.0130**
Firm Size: 5-20 employees	-0.0126**	-0.0035*	-0.0132**	0.0002
Firm Size: 21-50 employees	-0.0099**	-0.0018	-0.0079**	0.0001
Publica Firm	0.0643**	0.0823**	0.0478**	0.0647**
Temporary Help Agency	0.0796**	0.0845**	0.0687**	0.0982**
Part-time	-0.0235**	-0.0506**	-0.0134**	-0.0316**
Permanent Contract	-0.0323**	-0.0553**	-0.0286**	-0.0341**
Intermittent Permanent Contract	0.1190**	0.0894**	0.1575**	0.1063**
Employment Promotion Permanent Contract	-0.0258**	-0.0388**	-0.0280**	-0.0291**
GDP growth	-0.0070**	0.0050**	0.0400**	0.0534**
Receive UB	-0.0220**	-0.0124**	0.0286**	0.0452**
Receive UA	-0.1661**	-0.1657**	-0.1082**	-0.0899**
UB Entitlement Length	-0.1340**	-0.1687**	-0.1218**	-0.1421**
Quarters unemployed: 2 quarters	-0.1423**	-0.1405**	-0.1140**	-0.0957**
Quarters unemployed: 3-4 quarters	-0.2063**	-0.1648**	-0.1550**	-0.1130**
Quarters unemployed: 4-8 quarters	-0.3068**	-0.2080**	-0.2073**	-0.1653**
Quarters unemployed: 8-12 quarters	-0.3582**	-0.3152**	-0.2070**	-0.1753**
Quarters unemployed: > 12 quarters	-0.2289**	-0.3952**	-0.1553**	-0.1590**
Constant	0.4750**	0.4651**	0.3545**	0.2941**

Reference Group: Low Skill/Educated Worker aged above 45 working in the industry sector in a big private firm with a temporary contract. 13 sectoral indicators also included although not reported.
Statistical Significance: ** 99%, * 95%