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

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Abstract The Great Recession had led to gender convergence in unemployment rates. In this paper we seek its sources to assess whether this convergence will remain once the Great Recession ends. We use Social Security records to study the determinants of unemployment ins and outs for men and women separately, 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. We find that unemployment outs are crucial in understanding changes in unemployment rates in Spain as well as to understand the gender convergence in unemployment rates. Among the determinants of the large drop in unemployment outs, lack of demand and negative state dependence emerge as key sources, which affect men more negatively than women. In a scenario of upcoming recovery, unemployment outs will increase for short-term unemployed, particularly for males. On the contrary, both male and female long-term unemployed workers will face enormous difficulties to access a job, as the job access rates for long-term unemployed is not sensitive to the economic cycle. Hence, we expect that the gender convergence in unemployment rates will persist only when considering the long-term unemployed.

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1 Introduction

Empirical evidence indicates that in economic downturns women exhibit lower job loss and higher job finding rates than men (Elsby 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 (Elsby et al. 2010; Bachmann and Sinning 2012; Bachmann et al. 2014) and led to gender convergence in 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 and by recession (2008–2013) versus expansion (1997–2007). Our final aim is to seek into the sources underlying such convergence and eventually give an answer of whether this gender convergence in unemployment rates is likely to persist. For that purpose we analyse the underlying compositional versus non-compositional elements that explain the intensity of inflows and outflows in unemployment by gender and their corresponding differences between upturns and downturns of the economy. In particular, we proceed with two-step Oaxaca–Blinder decomposition analysis of these flows by gender in recession versus expansion and use the resulting estimations to simulate unemployment survival rates under different economic scenarios. We do so to explore the extent to which unemployment outs by gender are expected to react rapidly to an upcoming economic recovery or not. Although the analysis focuses on Spain, many of the results can be easily generalized to other continental labour markets where the big recession has led to important increases not only on the unemployment rate, but rather on 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 it is well above 50%.

This paper offers a clear contribution to the gender differentials literature (Elsby et al. 2010; Albanesi and Sahin 2013) since very few empirical studies have addressed the issue of the observed large differences in the ins and outs from unemployment by gender. The sharp gender convergence in the unemployment rate 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 and avoids ineffective policy responses or unintended increases in inequality.

This study also contributes to the empirical literature of unemployment ins and outs. Typically, previous empirical literature has addressed these questions 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.

Our findings indicate the following: First, convergence in layoff rates by gender is due to increases—by around 1.5 pp—of unemployment ins for men whereas these have remained barely constant for females. Positive selection in the composition of primarily female employed workers has smoothed their unemployment inflow rate during the recession. Indeed, sectoral composition emerges as one of the most important determinants in explaining the gender convergence in layoff rates. Secondly, we document a huge drop in job access rates in recession as compared to expansion, but much stronger for males than for females—the decrease reaches 15 pp. for men and 8 pp. for women. In line with previous research (i.e Elsby et al. 2013; Kroft 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. Thirdly, the large increase in the unemployment rate observed in the crisis is mainly caused by the large drop in unemployment outs. Finally, our simulations show that in a scenario of upcoming recovery, unemployment outs will increase for short-term unemployed and particularly for males since they respond more to cyclical forces. On the contrary, both male and female long-term unemployed workers will face enormous difficulties to access a job even in an upcoming expansionary context, as the job access rates for long-term unemployed is not sensitive to the economic cycle. Hence, we expect that the gender convergence in unemployment rates will persist only when considering the long-term unemployed.

The paper is organised as follows: Sect. 2 describes the data and presents descriptive evidence on job flows from and to employment. Section 3 presents the empirical approach to decompose the observed changes in unemployment ins and outs in recession versus expansion by gender. Section 4 presents estimates of the determinants of unemployment flows along with the two-step Oaxaca–Blinder decompositions and some simulations of the unemployment survival rates under different economic scenarios. Finally, Sect. 5 summarises the results and concludes.

2 The Database and Descriptive Evidence

We use an event history data set from Spanish Social Security records, the Continuous Working Live Sample (CWLS). It is compiled annually, and comprises a sample of over one million worker case histories (4% of all those registered). 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. Unfortunately, there is neither information on other household members, which would allow addressing intra-household labour market supply issues, nor additional firm information other than size and sector of activity.

We combine the annual samples available from 2005 to 2013 henceforth our database includes the complete labour market history of all individuals who came into contact for at least 1 day with the Social Security system—either as employees or as recipients of unemployment, pension or disability benefits—between 2005 and 2013. The final data used cover the working careers of these individuals aged 18–64 years over the period 1997–2013.

Two labour market statuses are considered: employed and unemployed. 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 inactivity (ie, retirement, disability and/or family care) which is discard from the analysis. 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.

Unemployment status includes all unemployed either receiving benefits or not. Our dataset allows us to compute the period of unemployment covered by UIB and 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 (2008) 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, each uncensored job spell is 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.[1] 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.[2] Our

[1] To avoid odd behaviour in the estimated baseline hazard functions due to the scarcity of observations spanning longer durations, we right-censor spells of unemployment longer than 48 months and spell of employment longer than 240 months.

[2] A monthly spell database becomes extremely demanding from the computational point of view given the long time span considered in the paper. 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.

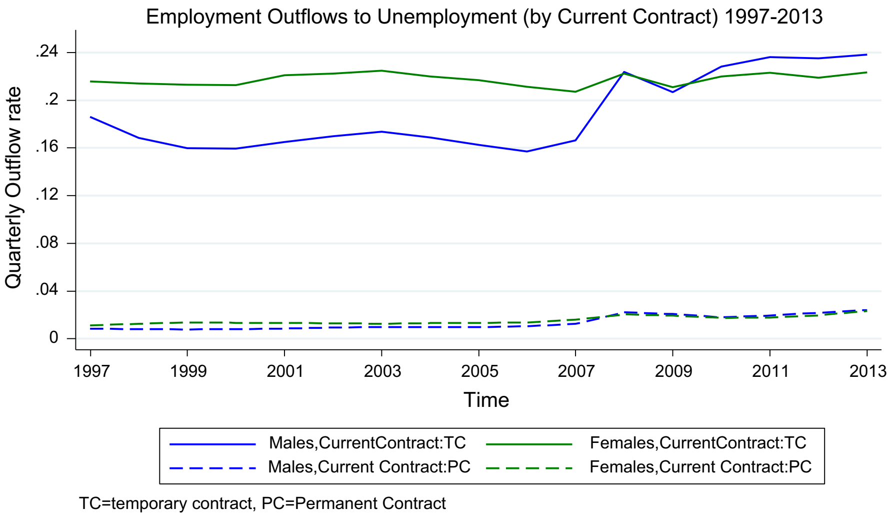

Fig. 1 Annual averages of quarterly unemployment inflows by gender and contract type

final sample consists on 1.676.144 unemployment spells (49.2% correspond to female workers) and 3.312.736 employment spells (46% corresponds to female workers).

2.1 Descriptive Evidence

2.1.1 Unemployment Ins: Layoffs

Figure 1 describes annual averages of quarterly unemployment inflows from 1997 to 2013 by gender and contract type.[3] The first point to be made is that 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. 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, women experience higher rates of unemployment inflows than males up to 2007, but from the start of the recession onwards the layoff probability increases less for women than for men. These worked on average in jobs with lower rotation rates in the pre-recession period.

Table 1 shows that the recession leads to a change in the composition of job spells given that the share of long tenure job spells, with indefinite contracts located in medium and large firms that require higher skills increases whereas the share of short-duration fixed-term jobs that require lower skills decreases notably. This is because

[3] 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.

Table 1 Distribution of job spells (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 tenure	37	46	38	44
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 types				
Full-time TC	31	29	26	24
Full-time PC	69	70	73	75
Part-time	21	5	27	9
Temporary help agency sectors[a]	1.3	1.2	0.7	1
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	42	33	51	71
Education				
Less than primary	10	18	9	14
Less than secondary	30	36	29	35

Table 1 continued

	2000–2007		2008–2013	
	Females (%)	Males (%)	Females (%)	Males (%)
Secondary	34	29	32	30
University	24	15	28	19
Job qualification				
High skill	18	14	20	16
Medium skills	30	25	30	26
Low skills	51	60	48	56

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

PC permanent contract, *TC* temporary contract

[a] We restrict to the general regime

layoffs, mainly those at early stages of the recession, are concentrated in low-skilled, short-duration jobs associated with fixed-term contracts.[4] The main difference between men and women seems to be that layoffs from these low quality jobs—i.e low-skilled jobs with fixed-term contracts at small firms-, are more intense for men.

2.1.2 Unemployment Outs: Job Access

Figure 2 depicts annual averages of quarterly unemployment (non-employment) outflows by gender and by contract type in the new job. The rate of access to indefinite 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. Descriptive statistics for job access are presented in Table 4 and they show that male workers from certain sectors (construction) and occupations (low-skills) suffered a large drop in the job finding probability.

This scenario is fully consistent with the trend in unemployment rates observed in the Spanish economy (Fig. 3). Before 2008, unemployment rates among women are higher than among men as women are 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.

[4] Table 2 presents layoff rates by gender and by job and individual characteristics. Upturn and downturn periods are presented separately.

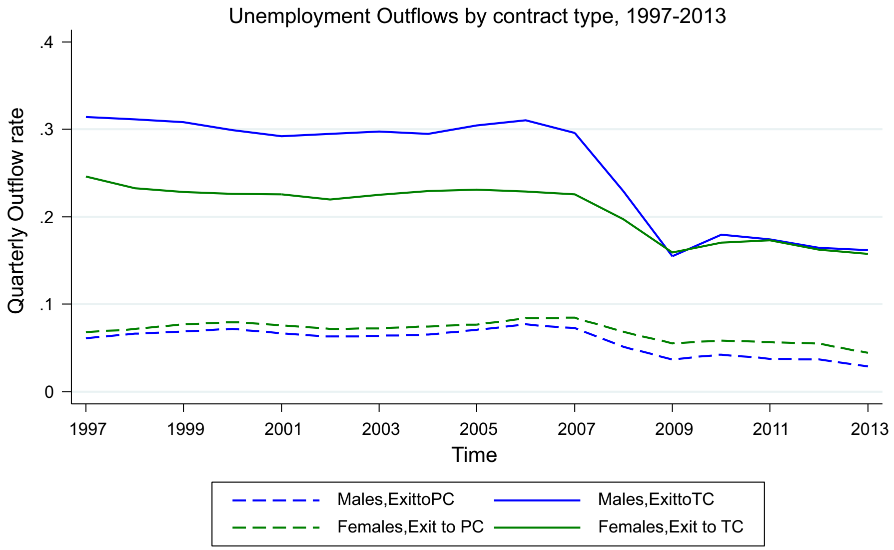

Fig. 2 Annual average of quarterly unemployment outs by gender and contract type

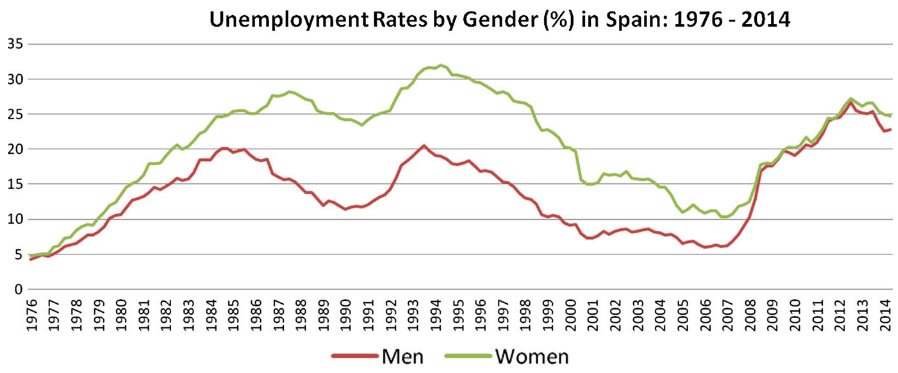

Fig. 3 Unemployment rates by gender

The trends just presented for the current big recession are not exclusive of the Spanish economy.[5] 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 also large, around 20 pp. (from 40 to 20%). However, the gender gap differential observed in the downturn in US is mostly explain by differences in the behaviour of job separation probabilities and not on job finding probabilities.

[5] 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) finds 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%.

Table 2 Quarterly layoff rates by sample characteristics—females versus males and expansion versus recession

Total	Layoff rate			
	2000–2007		2008–2013	
	Males (%) 5.5	Females (%) 7.4	Males (%) 7.2	Females (%) 7.5
Age				
<30	10	12	14	14
30–45	4.2	6.0	6.5	6.7
>45	2.8	4.3	4.1	4.5
Contract types				
TC	16	21	22	22
PC	0.9	1.3	2.0	1.9
Part-time	12	10	13	10
Public firm sectors	10	10	19	14
Agr	7.8	10.1	15	14
Ind	3.7	7.7	4.5	6.6
Construction	9.5	5.9	15	7.8
Commerce + hotels	5.6	9.4	7.4	9.6
Transport + communications	3.7	6.1	5.5	6.5
Financial servs	0.8	1.7	1.3	1.7
Construction servs	9.3	9.7	7.8	6.5
Rent serv. + computers + tech. servs	7.4	8.7	7.6	8.0
Education + health + culture	6.6	5.9	6.2	6.3
Other services	5.9	5.8	4.9	6.5
Firm-size				
<10	8.8	8.6	11	9.8
>10<50	6.2	7.2	6.8	7.4
50–100	5.8	7.4	5.9	7.2
>100	4.6	6.2	4.6	6.2
Education				
Less than primary	7.4	9.9	11	11
Less than secondary	6.2	8.9	8.7	9.2
Secondary	4.2	6.1	5.2	6.3
University	4.1	6.3	3.9	5.6
Job qualification				
High skill	1.8	3.8	2.5	4.3
Medium skills	2.5	4.2	3.9	4.9
Low skills	7.7	10.6	10	10

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

PC permanent contract, *TC* temporary contract

Lastly, given that unemployment ins and outs remain relatively constant within the years of expansion and recession respectively, from now on we divide the whole analysis into two periods: the upturn[6] (2000–2007) and the downturn (2008–2013). Our empirical strategy consists of estimating the determinants of unemployment ins and outs by gender and by these two periods (upturn and downturn) and then, break the average differentials in predicted flows down into characteristics (composition effects) and difference in coefficients (non-compositional or behavioural effects).

2.2 The Contribution of Unemployment Ins and Outs to the Unemployment Rate

Before moving to the analysis of the determinants of unemployment ins and outs by gender and by these two periods (upturn and downturn), we document the extent to which the recent upswings in unemployment are due to increases in unemployment ins and/or to declines in unemployment outs. This analysis is based on the dynamics of steady state unemployment (u^{ss}).

$$u_t^{ss} = \frac{\lambda_t^{EU}}{\lambda_t^{EU} + \lambda_t^{UE}} \tag{1}$$

where the terms λ^{EU} and λ^{UE} represent the instantaneous probability of finding and losing job, respectively. Based on US data, Shimer (2012) shows that Eq. (1) provides a very good approximation of the end-period unemployment rate since the correlation between the estimated u^{ss} and the unemployment rate was 95% for the last two decades. For Spain, the correlation between the 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.

To compute the relative contribution of the two transition rates on the unemployment rate we follow the approach used in Petrongolo and Pissarides (2008) and Elsby et al. (2013). 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 presented in Fig. 4 indicates 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.

In particular, we find that 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. This will be used in the last section in the paper, as we will focus on unemployment outs rather than on unemployment ins when

[6] Though in the statistical section we have shown the time interval 1997–2013, in the estimation we will restrict the analysis for the upturn to the years 2000–2007.

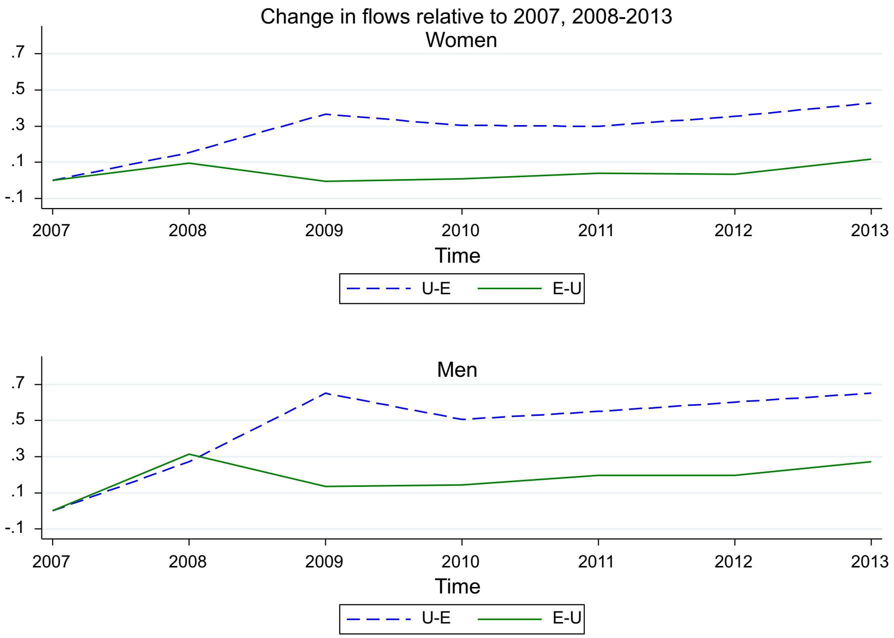

Fig. 4 Change in ins and outs of unemployment during the crisis

we speculate about the prospects of Spanish unemployment levels in an upcoming recovery setting.

3 Two-Step Blinder–Oaxaca Decomposition in Unemployment Flows: Empirical Approach

To dig deeper into the determinants of gender differentials in unemployment flow dynamics we firstly estimate the layoff and job finding transition probabilities by gender and for the two periods under analysis. Secondly, we apply a two-step Oaxaca–Blinder decomposition for each transition, trying to identify whether differences in coefficients (non-compositional effects) versus changes in the characteristics (compositional effects) drive the observed trends. In the following lines we explain in more detail each step of the analysis.

Firstly, we estimate the hazard rate $h\ (t/\Omega)$ by gender and for the two periods under consideration (for simplicity we omit indexes):

$$h\ (t/\Omega) = h_0(t)F\ (\beta X(t) + \varepsilon(t)) \tag{2}$$

The term $h_0(t)$ stands for the duration dependence term and it is modelled using a set of dummy variables (five and six dummies for the unemployment and employment hazard rate, respectively). Within the set of $X(t)$ covariates we have individual characteristics, job and firm characteristics, cyclical information. Within individual characteristics we include age (three categories), nationality, family composition, labour market experience, the receipt and length of benefits, educational attainment levels (three levels) and whether the worker was recalled. Within job characteristics we include sector of activity (15 sectors), type of contract (four types), hired by a temporary help agency, job qualification (10 categories), firm's ownership (public versus private) and firm's size (four categories). The business cycle is represented by the quarterly GDP growth rate and regional dummy variables. All these covariates are common to the unemployment and employment states except for those related to the unemployment benefit system, which are only considered for the case of the unemployment state.

We estimate hazard rates, instead of unconditional transition probabilities, so as to best gauge the relevance of state duration dependence in explaining gender differences in the behaviour of job separation and job finding probabilities. 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.[7] The Blinder–Oaxaca decomposition suffers from an identification problem when dummy variables are included in the model and this affects the interpretation of the decomposition.[8] To solve this identification problem, we use the variant introduced by Gardeazabal and Ugidos (2004) (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.

First-step decomposition: Using previous model estimates as our inputs we apply the Oaxaca–Blinder decomposition. The *first-step decomposition* consists of computing changes in average flows between recession and expansion by gender ($g = f, m$). Let's assume that the term X contains all the covariates used in the estimation.

$$\begin{aligned} R_g &= \left(\overline{h}_{t_1 g} - \overline{h}_{t_0 g}\right) = \left(\overline{X}_{t_1 g}\hat{\beta}_{t_1 g} - \overline{X}_{t_0 g}\hat{\beta}_{t_0 g}\right) \\ &= \left(\overline{X}_{t_1 g} - \overline{X}_{t_0 g}\right)\hat{\beta}_{t_1 g} + \left(\hat{\beta}_{t_1 g} - \hat{\beta}_{t_0 g}\right)\overline{X}_{t_0 g} = \overline{E}_g + \overline{C}_g \end{aligned} \tag{3}$$

where R_g refers to the "Raw" difference in the corresponding transition probability in an upturn (t_1) versus a 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.

[7] Bachmann and Sinning (2012) also use the linear probability model 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.

[8] 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.

Second-step decomposition: 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 the corresponding transition 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:

$$R_f - R_m = \left(\overline{h}_{t_1 f} - \overline{h}_{t_0 f}\right) - \left(\overline{h}_{t_1 m} - \overline{h}_{t_0 m}\right) = \left(\overline{E}_f + \overline{C}_f\right) - \left(\overline{E}_m + \overline{C}_m\right) \quad (4)$$

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

4 Results from the Two-Step Decomposition

4.1 Unemployment Ins

Results from the estimation of the layoff rate by gender and for the two periods under consideration can be found in Table 6 ("Appendix"). Once the GU identifying correction is applied, the two-step decomposition of layoff rates is presented in Table 5.

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—*first-step decomposition*. The last two columns decompose gender differences in differences in layoffs (recession versus expansion) into composition and non-compositional effects—*second-step decomposition*.

As depicted in Fig. 4, 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 composition effects seem to lead to a decrease in layoffs whereas differences in coefficients seem to lead to the opposite.[9] Table 4 reveals that compositional changes seem to lead to a large decline in the 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 in medium or large firms, which explains their lower layoff rates in this period compared with the expansionary one. Similarly, Bachmann and Sinning (2012) find also that in US increases in job tenure and educational attainment levels reduce unemployment inflows in recessions. 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.

[9] Using the conditional log–log function to estimate the layoff 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.

In particular, we obtain that for men the drop in the share of jobs in the construction sector explains 6.3% of the compositional component

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 Fig. 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 (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.[10] 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.

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. 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 (15.6%) and job qualifications (11%).[11] Indeed, 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.

To summarize, overall, unemployment ins have remained barely constant for females but rather have increased by around 1.5 pp for males leading 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 almost 20% 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-education increase the layoff probability in the downturn relative to

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

[11] Indeed, in the detailed composition for men, the non-compositional factors are 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.

Table 3 Unemployment exit rates by gender and by recession versus expansion

Total	2000–2007		2008–2013	
	Males (%) 36%	Females (%) 31%	Males (%) 21%	Females (%) 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 qualification				
High skill	28	38	20	28
Medium skills	29	30	20	22
Low skill	38	30	22	22

the upturn. This last effect has been 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 and henceforth we do not expect this convergence to remain for the new upturn. Note however, that the higher job destruction in low skill and temporary workers and in the construction sector, the main drivers of this convergence in layoff rates, will not last forever. Layoff rates in post-sample time interval-2014, although not displayed, point into this direction.

4.2 Unemployment Outs

The results of the estimations for the Unemployment Outs are displayed in Table 7.[12] and the results of the two-step decomposition are displayed in Table 5.

We observe 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 large as for women (15 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.[13]

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 workers accounts for around 33% of the compositional effects and 18–19% of the raw differential in the job finding probability in the recession compared to the expansionary period. As the recession continues, the share of short-term unemployed gradually falls which increases the share of long-term unemployed. Also, due to negative state dependence in the unemployment hazard rate, as duration of unemployment increases, the probability of finding a job decreases. This might be due to depreciation of human capital skills, stigmatization of workers, decreasing search effort, or lose of social networks. Thus, for any of these reasons, an increasing pool of long-term unemployed may generate hysteresis and slow down future reductions in the unemployment rate. Bachmann and Sinning (2012) also show that changes in the duration of unemployment seem to be a special feature of deep recessions. In particular, they 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

[12] Table 7 presents the detailed estimation of the job finding probabilities by gender and for expansion and recession. 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. 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.

[13] 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.

Table 4 Unemployment ins: decomposition of the estimation of the layoff probability by gender and by recession versus expansion

Unconditional difference	Women		Men		DD (women–men)	
	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
Immigrant	−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[a]	0.0001	−0.63	−0.0001	0.37	0.0002	−6.7
Job qualification	−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

Table 4 continued

Unconditional difference	Women		Men		DD (women–men)	
	0.00045		0.0149		−0.0158	
	Absolute contribution	Relative contribution (%)	Absolute contribution	Relative contribution (%)	Absolute contribution	Relative contribution (%)
Experience	0.0002	0.83	−0.0045	−8.1	0.0047	−36.0
Immigrant	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 qualification	−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

[a] 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 5 Decomposition of the estimation of the job finding probability by gender—LPM (recession versus expansion)

Unconditional difference	Women		Men		DD (women–men)	
	−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

Table 5 continued

Unconditional difference	Women		Men		DD (women–men)	
	−0.0813		−0.1499		0.0686	
	Absolute contribution	Relative contribution (%)	Absolute contribution	Relative contribution (%)	Absolute contribution	Relative contribution (%)
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

what might exacerbate the hysteresis problem converting a large share of cyclical unemployment into structural unemployment.

Second, as expected, the drop in aggregate demand, proxy by GDP growth, also explains the observed drop in the job finding probability. 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).

Similarly to Elsby 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: benefit coverage (contributory and assistant) and average length of benefit entitlement are both higher in recession versus expansion. Benefit coverage was higher at the earlier stages of the recession because new entrants into unemployment had more labour market experience and tenure than those who enter into unemployment during the expansionary period, and hence it was also higher their probability of being entitled to benefits. There is ample evidence that receiving unemployment benefits delays job finding as a consequence of a decrease in search intensity or an increase in the reservation wage.[14] With regards to the relevance of the length in the entitlement period note that the lack of job offers in the recession has led to a higher proportion of workers who exhaust their unemployment benefits.

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. 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.

The results just presented 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.[15] This result is in line with the one presented in Shimer (2012) who concludes that observable changes in the composition of the unemployed population in term of their observable characteristics 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 that leads to a drop in the job finding probability is the negative state dependence structure of the unemployment hazard. Indeed, the negative effect of elapsed unemployment duration on the job finding probability explains 34.4% of the non-compositional effects for women and 43.4% for men. Moreover, the detailed

[14] 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 a similar dataset.

[15] That is, if groups that 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. We obtain that the variation in the composition of entrants is insufficient to drive the variation observed in aggregate unemployment duration.

decomposition of the state dependence structure of the unemployment hazard rate 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 the downturn relative to the previous upturn, whereas the job finding probability for long-term unemployed hardly changes. Interestingly, Song and Von Wachter (2014) and Elsby et al. (2013) also find for US that the exit rates for long-term non-employment do not exhibit strong cyclical movement. This result just presented, help us to better understand the evidence of the hysteresis process mentioned before. We find that during the current Big Depression, short-term unemployed workers have faced an important drop in their job finding probability increasing the pool of long term unemployment. Once the economic recovery starts, the job finding probability of short-term unemployed might move back to pre-recession levels but since long-term unemployed do not seem to exhibit high sensitivity to the economic cycle, their job finding probability will remain low exacerbating the problem of structural unemployment already present in the Spanish economy.

It is also remarkable to note that the contribution of benefits to the non-compositional effects is negative, i.e., does not contribute to explain the observed drop in the unemployment exit rate. That is, conditional on receiving benefits, the probability of exiting from unemployment has been even higher in recession than in expansion. This is because during the crisis, the disincentive effects or the moral hazard effect of benefits has probably 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 hypothesis that the unemployment benefit system should be particularly important to explain the large drop in the job finding probability. This is in line with recent research that suggests only modest impacts of UI extensions on the search effort and duration of unemployment of unemployment insurance recipients (Schmieder et al. 2012). Much of the impact of unemployment insurance on job search comes from reducing liquidity constraints than traditional job search disincentives.

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 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 gender convergence in job finding rates.

In view of these results, our findings about the gender convergence in the unemployment outs in the downturn with respect to the previous upturn can be summed up as follows: First, we find that compositional and non-compositional effects are similarly important to explain this gender convergence. Second, lack of demand, a higher share of long-term unemployed, the fall in the unemployment exit probability for short-term unemployed, and the drop in the unemployment exit probability for workers from the construction sector, are the main sources of this gender convergence in unemployment outs. Some of these components are mainly pro-cyclical (i.e lack of demand and fall in the unemployment exit probability for short-term unemployed) whereas others might has a more structural flavour (i.e higher share of long-term unemployed, and the drop in the unemployment exit probability for low-skills workers and workers from the construction sector).

4.3 Will Unemployment Convergence by Gender Persist in the Upcoming Recovery? A Counterfactual Exercise

The reduced form approach used in the paper does not allow us to determine whether the observed changes in unemployment rates and their gender differentials are purely cyclical or structural. A range of possible sources of hysteresis are sectoral mismatching, extension of unemployment insurance, negative state dependence and an increasing proportion of long-term unemployed (Shimer 2012; Lazear and Spletzer 2012; Elsby et al. 2010). These authors find no clear evidence of unemployment outs being led by these structural sources. Nevertheless, unemployment persistence is far more significant in European countries and hence, structural factors might be more relevant.

The results presented for the unemployment outs are mixed in this respect. The lack of demand and the lower exit probability of short-term unemployed, are both mainly cyclical and hence, the observed gender convergence might vanish when the recovery starts. On the contrary, the other two key factors identified (higher share of long-term unemployed, and the drop in the unemployment exit probability for low-skills workers and workers from the construction sector) might slow down the unemployment outs for men in the medium and long-run. In terms of the number of workers, the construction sector in Spain was the largest among the Member States in 2007 but in the near future it is not expected to return to its pre-crisis levels. The problem of the long term unemployed is that the longer people remain unemployed, the more difficult and costly it is to reintegrate them into employment. This might be particularly relevant given that the recovery might be driven by new growth sectors, which requires a shift in skill requirements vis-à-vis pre-crises growth patterns. This also increases the risk that some male jobseekers will drop out of the labor market.

Our model can be used to predict the speed at which male and female unemployment rates are expected to decrease in the context of an upcoming recovery, and hence, speculate on their expected gender differentials in the eventual new economic context. To that end, and given the provided evidence that unemployment rates are primarily lead by unemployment outs rather than ins, 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 whether men or women will benefit differently from it.

Our specific purpose is to illustrate the potential importance of the compositional aspect for job access in the context of an eventual recovery since these compositional factors might be a sign of persistent or structural unemployment. Subsequently, 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 potential differences in the dynamics of the pool of female versus male unemployed workers at the onset of the economic recovery. More specifically, we simulate unemployment hazard rates for both men and women for 12 consecutive quarters (3 years) under the following five scenarios:

1. Scenario 1 (expansionary pre-recession context): composed by the pool of unemployed workers in 2007 and parameter estimates from the 2000 to 2007 model.
2. Scenario 2 (expansionary pre-housing boom context): composed by the pool of unemployed workers in 2003 and parameter estimates from a model using the period 2000–2003, that is, an expansionary context without the specific features of the final stage of the housing boom.
3. Scenario 3 (recession context): composed by 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 from a model 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.[16]
4. Scenario 4 (counterfactual 1): composed by the pool of unemployed workers in 2013 and parameter estimates from a model estimated using the 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. For GDP growth, we do the same as in scenario 3.
5. Scenario 5 (counterfactual 2): composed by the pool of unemployed workers in 2013 and parameter estimates 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. For GDP growth, we do the same as in scenario 3.

Each worker's unemployment spell is simulated 1000 times over a 12-quarter period. From each simulation we can construct individual male and female unemployment dynamics, which are then used to compute survival probability rates in each quarter (Fig. 5). 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 males and females with different unemployment durations at the time when the simulation starts. We divide the pool of unemployed workers into four groups: (1) unemployed for 1–6 months; (2) unemployed for 7–12 months; (3) unemployed for 13–24 months; and (4) unemployed for 25–36 months. The panels of Fig. 6 represent survival rates in unemployment for each group of unemployed workers for a 12-quarter (3-year) interval and for the five different scenarios described above.

[16] 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.

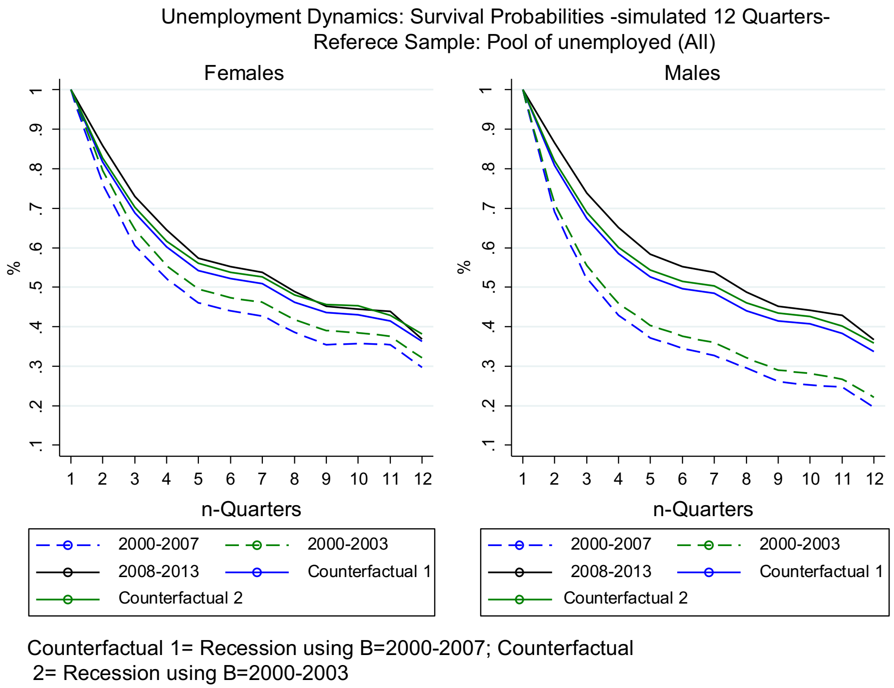

Fig. 5 Unemployment survival rates along 12 quarters—all unemployed workers in the sample

Figure 5 reveals the following:[17]

- 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 women. In an expansionary period, such as the one Spain enjoyed in 2000–2007, after 4 quarters (1 year) more women than men would remain unemployed (52% of women and 42% of men). But in a context of recession these survival rates would increase for both but much more for men (68% for women and 65% for men).
- Second, the two counterfactual exercises illustrate that even in an expansionary context, the characteristics of the pool of unemployed workers in 2013 would delay unemployment outs to a great extent. This is because the share of long-term unemployed is much higher in recession than in the expansionary context whereas the unemployment exit probability for long-term unemployed hardly changes with the cycle. This is so for both men and women but it is clearly more important for men. The estimated survival rates in the two counterfactual contexts closely

[17] It can be checked how far the Spanish scenario by the end of 2014 (which is already known) resembles any of those depicted in Fig. 6: 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.

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 Fig. 6 represent estimated survival rates for workers with short unemployment durations (<6, and 7–12 months), whereas the last two represent estimated survival rates for the long-term unemployed (1–2, 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 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. We already has shown that the unemployment exit probability for short-term unemployed is highly sensitive to the business cycle, especially for men.

These results lead us to conclude that in any upcoming recovery unemployment outs will particularly affect positively short-term male unemployed workers. Hence, we would expect that the observed gender convergence in unemployment outs will disappear in the short-run for the sample of short-term unemployed. However, for long-term unemployed individuals, both males and females will keep facing enormous difficulties in accessing jobs in the next upturn. 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 in other sectors, are expected to alleviate this problem.

5 Summary and Conclusions

This paper compares gender differences in the behaviour of unemployment ins and outs in Spain in the Great Recession with the previous upturn (2000–2013). This is done by using a longitudinal database extracted from Social Security Records 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 leading to a convergence in layoff rates by gender. To understand the underlying process, it must be noted that the current

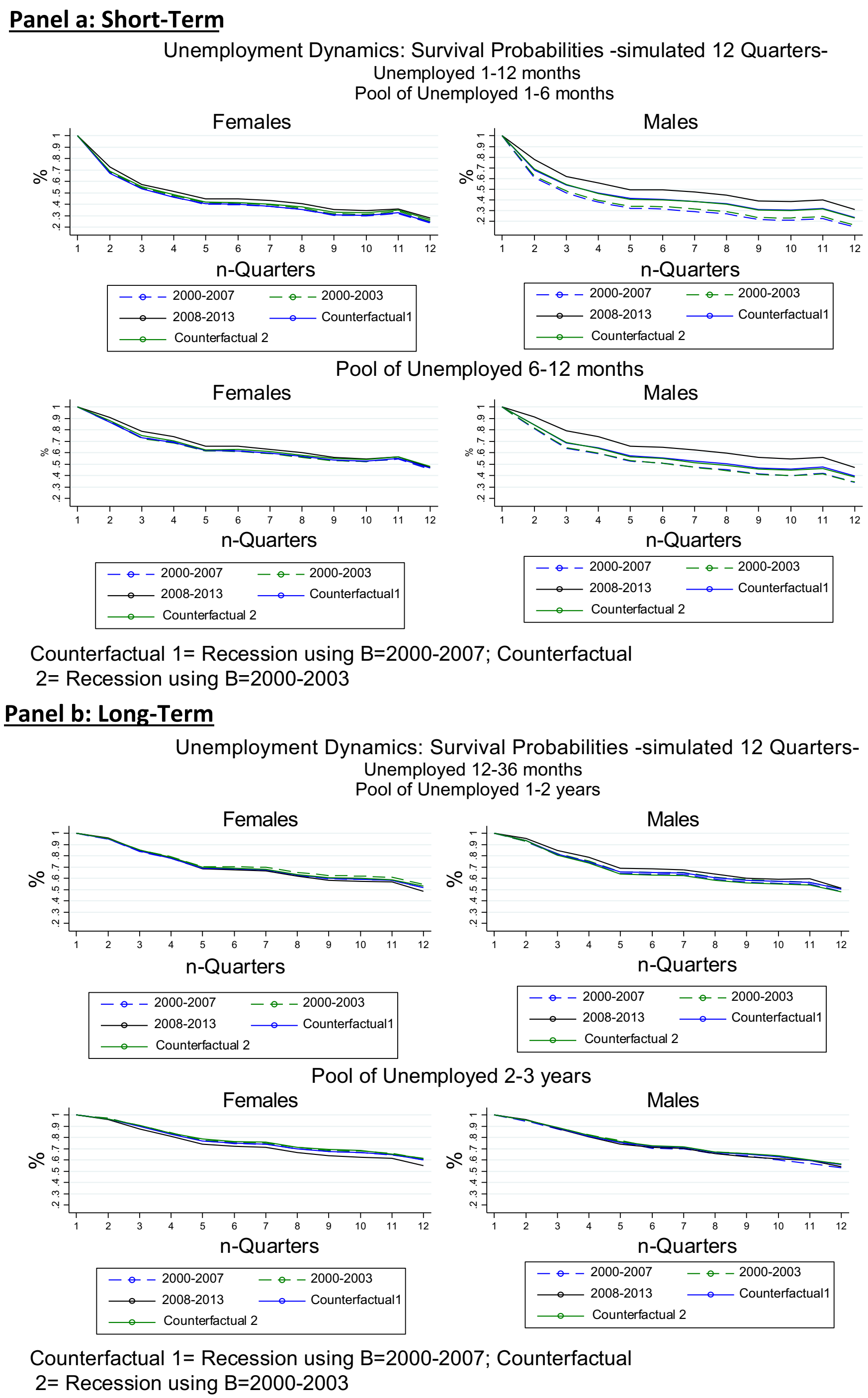

Fig. 6 Estimated unemployment survival rates by duration of unemployment

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 almost 20% 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, but gender differences are noticeable: the probability of finding a job has decreased by around 15 pp. for men and 8 pp. for women what explains the observed convergence in job access rates by gender in the last years. Second, among gender differences in the determinants of this drop, we find that lack of demand, and increased share of long-term unemployed, a drop in the unemployment exit probability for short-term unemployed and being unemployed from the construction sector are identified as the main sources of this convergence in the recent downturn compared to the previous upturn. Some of these components might be considered as affecting the structural component of the unemployment rate.

Our simulations show that in any upcoming recovery unemployment outs will benefit particularly short-term male unemployed workers, as males respond more to cyclical forces than women. This leads us to speculate that gender convergence in unemployment rates will not persist for short-term unemployed workers. However, these amount only to 36% of total unemployed workers. We find that both male and female long-term unemployed (the remaining 64%), will face enormous difficulties to access a job even in an expansionary context. For these, the rate of unemployment is expected to remain high for many years, even in a strong recovery framework. No significant gender differentials are found for the group of the long-term unemployed. Implementation of successful, active policies directed at retraining, job-search consulting programs and relocating both male and female Long-Term Unemployed workers are, undoubtedly, required to alleviate this problem.

Compliance with Ethical Standards

Conflict of interest The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Appendix

See Tables 6 and 7.

Table 6 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**

Table 6 continued

	2000–2007		2008–2013	
	Females	Males	Females	Males
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**
Temporary 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 months	0.1518**	0.1208**	0.1525**	0.1472**
Tenure: 4–6 months	0.1302**	0.0951**	0.1336**	0.1112**
Tenure: 7–12 months	0.0774**	0.0542**	0.0732**	0.0512**
Tenure: 13–24 months	0.0481**	0.0362**	0.0377**	0.0275**
Tenure: 25–36 months	0.0454**	0.0332**	0.0351**	0.0246**
Tenure: 36–60 months	0.0353**	0.0270**	0.0259**	0.0195**
Constant	0.1408**	0.1256**	0.1232**	0.1323**

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%

Table 7 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**
Immigrant	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: third class officials	0.0224**	0.0177**	0.0130**	0.0175**

Table 7 continued

	2000–2007		2008–2013	
	Females	Males	Females	Males
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%

References

Albanesi, S., & Sahin, A. (2013). *The gender unemployment gap*. CEPR discussion papers 9448.

Bachmann, R., & Sinning, M. (2012). *Decomposing the ins and outs of cyclical unemployment*. IZA discussion papers 6362, Institute for the Study of Labor (IZA).

Bachmann, R., Bechara, P., Kramer, A., & Rzepka, S. (2014). *Labour market dynamics and worker heterogeneity during the great recession—Evidence from Europe*. Ruhr economic papers 0499, Ruhr-Universität Bochum.

Elsby, M., Hobijn, B., & Sahin, A. (2010). The labour market in the great recession. *Brookings Papers on Economic Activity*, *41*(Spring), 1–69.

Elsby, M., Hobijn, B., & Sahin, A. (2013). Unemployment dynamics in the OECD. *The Review of Economics and Statistics*, *95*(2), 530–548.

Fortin, N., Lemieux, T., & Firpo, S. (2011). Decomposition methods in economics. *Handbook of Labor Economics*, *4*(A), 1–102.

García-Pérez, J. I., & Rebollo-Sanz, Y. F. (2014). Are unemployment benefits harmful to the stability of working careers? *The case of Spain. SERIEs*, *6*(1), 1–41.

Gardeazabal, J., & Ugidos, A. (2004). More on identification in detailed wage decompositions. *The Review of Economics and Statistics*, *86*(4), 1034–1036.

Kroft, K., Lange, F., Notowidigdo, M. J., & Katz, L. F. (2014). *Long-term unemployment and the great recession: The role of composition, duration dependence, and non-participation*. NBER working papers 20273, National Bureau of Economic Research.

Lazear, E. P., & Spletzer, J. R. (2012). The United States labor market: Status quo or a new normal?. In *Proceedings of economic policy symposium—Jackson hole*, Federal Reserve Bank of Kansas City, pp. 405–451.

Petrongolo, B., & Pissarides, C. A. (2008). The ins and outs of European unemployment. *American Economic Review*, *98*(2), 256–262.

Rebollo-Sanz, Y. F. (2012). Unemployment insurance and job turnover in Spain. *Labour Economics*, *19*(3), 403–426.

Schmieder, J. F., Von Wachter, T., & Bender, S. (2012). The long-term effects of UI extensions on employment. *American Economic Review*, *102*(3), 514–519.

Shimer, R. (2012). Reassessing the ins and outs of unemployment. *Review of Economic Dynamics*, *15*(2), 127–148.

Song, J., & Von Wachter, T. (2014). *Long-term nonemployment and job displacement*. Jackson Economic Policy Symposium—Jackson Hole Symposium.