Do Employment Opportunities Decrease for Unemployed Older Workers?[☆]

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Abstract

Increasing the labour market participation rates of older workers is a means to secure the sustainability of public finances. However, questions about behaviour of unemployed older workers and their employment prospects remain. This paper investigates why workers, aged 50 or over, have less employment opportunities when they grow older. Using a competing risks model on British panel data, we examine the chances of re-employment after unemployment spells for older individuals. We find that human capital characteristics and economic incentives play an important role in the re-employment chances of older unemployed workers. We show that the probability of returning to employment after an unemployment spell decreases as workers get older. An Oaxaca type decomposition supports the role of age in the unemployment duration gap between 'older' and 'younger' individuals. The duration of leaving unemployment to employment of older workers would be lower if they will be treated in the same way as the younger ones, which is consistent with elderly employment barriers.

Keywords: Older workers, Labour Supply, Employment, Unemployment, Retirement age, Panel data, Duration model, Discrimination.
JEL: J14, J21, J64, J70.

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1. Introduction

Ageing population raises many concerns about the sustainability of public finances. With more and more older people, financing health and pension systems is one of the challenges for developed countries. This situation is strengthened by the low employment rate of elderly workers, aged 50 or over. Although the position of workers aged between 50 and State Pension Age in Great Britain has been improved since 1992 (Figure 1), this overall picture hides the decline of participation rates of workers over 55. At the same time, unemployment rates of workers in their fifties have increased steadily since the Great Recession. While older people are less exposed to unemployment than those of prime-age, older job seekers experience difficulties to reintegrate the labour force after a certain age. Almost one of two unemployed workers aged 50 or over is out of employment for a year or more, which is higher than for any other age (Figure 2). They are likely to be unemployed for 5.8 weeks longer than those aged between 30 and 49, and 10.6 weeks longer than those aged between 20 and 29, and the probability of getting an employment decreases by 2.6 percent for each additional year in age (Wanberg et al. (2015)).

The main objective of this study is to determine whether older workers have difficulties to remain in employment because of their age. We focus on workers aged 50 or above, whom we refer as older workers, and we want to know whether the opportunities to re-enter in the job market decrease with age. Understanding the pattern of the individual's employment decisions when approaching the retirement age is crucial for both economic and social reasons. The difficulties encountered on the labour market and their consequences on the economy have pushed the authorities to reform the labour market. Many countries have already increased the official retirement age, i.e. the minimum age at which individuals can claim a State Retirement Pension which is going to increase to 66 by October 2020 for both men and women in UK, and seek policies which aim to increase the labour market participation of older workers. Despite older workers facing more difficulties finding an employment, they are encouraged to remain in the labour force.

This paper explores the pathways facing seniors near retirement in Great Britain using a discrete-time independent competing risks models. The objective of this paper is to evaluate why individuals have less employment opportunities as they grow older by investigating *unemployment duration* until an exit into employment occurs. One contribution of this analysis is to use a discrete-time duration model not extensively applied in retirement studies. Moreover, transitions from unemployment depend on observed and unobserved heterogeneity, as well as on time spent in unemployment state, modeled in a flexible way without imposing any assumption on the functional form. Another contribution of the paper is to emphasize on the labour supply of unemployment workers. Previous studies on labour market decisions of seniors have been particularly concerned by early retirement issues and the transitions from employment to retirement (Gruber and Wise (2004), Oswald (1999), Schils (2008)). In the current paper, the approach is focused on evaluating employment opportunities at older ages through exits from unemployment to employment. Finally, we contribute by studying the role of age on labour market transitions of older unemployed workers by simulating unemployment duration for workers with different age groups. Despite the fact that factors influencing the labour market for older workers have extensively been studied, few attention has been given to the role of age on employment opportunities.

Our results indicate that human capital characteristics and economic incentives play an important role in the re-employment of older workers. We also find that the probability of being in employment decreases with the age. Workers are less likely to be re-employed because of their age. The Oaxaca type decomposition supports the role of age in the unemployment duration gap between 'older' and 'younger' workers. The unemployment duration of older workers would be lower if they will be treated in the same way as the younger workers. Older unemployed individuals face reduction opportunities on the labour market as they grow older, which is consistent with age discrimination or elderly employment barriers. The conclusions are robust to alternative specifications.

The paper proceeds as follows. We begin the paper by first presenting a survey of the related literature. Section 3 gives an overview of the social institutions in Great Britain which can influence the labour market of older workers. Sections 4 and 5 describe the dataset, and the empirical approach used to address these issues. Section 6 assesses the hazard rate from unemployment to employment. Section 7 presents the estimation results of the simulation for duration spent in unemployment before concluding.

2. Theoretical Considerations and Previous Studies on Employment Decisions

A large body of literature explains the important effects of human capital on labour market opportunities of individuals. Educational attainment and training play a role on labour market participation, at every stage of life. Human capital increases workers' productivity, implying higher earnings. Individuals who invest in human capital (education, training, etc) are supposed to stay longer on the labour force (Becker (1964), Lemieux (2006)). Moreover, studies have shown that workers well educated are less prone to unemployment risks, i.e. they have lower probability of becoming unemployed at a specific time relatively to workers with a low level of education. The pioneering studies of Nickell (1979) for Great Britain, or Mincer (1991b), Mincer (1991a) for the United States have found that higher education level reduces unemployment incidence and unemployment duration. Nickell (1979) uses a hazard rate framework to model how education affects the incidence and duration of unemployment. He finds that educational level plays an important role by reducing unemployment incidence for British workers. Mincer (1991b), Mincer (1991a) decomposes the unemployment rate into different parts (i.e. into the probability of having separated from the previous job, the probability of experiencing unemployment when job loss, the duration of unemployment for job losers, the labour force rate and the labour force participation rate), and he demonstrates that school attainment lowers unemployment incidence and unemployment duration in the United States.

Health state can also affect the employment decisions of older individuals. Health can be considered as a component of human capital, and investing in health increases the workers'productivity level (Grossman's model). Hence, having a poor health is associated with a lower productivity, involving a lower labour income and decreases the likelihood of labour force participation. Many studies on ageing have supported the idea that health is an important determinant of retirement decisions. They find that having a poor health, a lack of education or being aged increase the likelihood of leaving the labour force (Berkovec and Stern (1991), Gannon and Roberts (2011)).

Among the other determinants that can explain older workers' participation in labour market is the effect of employment policies through the influence of financial pension incentives. The literature has studied the impact of these economic factors on labour supply behaviour of workers in a wide range of countries, and showed evidence of their impact on labour force participation (Gruber and Wise (1998), Gruber and Wise (2004)). A common result indicates that social assistance increases the probability of exiting labour market. More generous unemployment benefits are associated with longer unemployment spells and hence a lower probability of moving back to employment through a decline of job search effort (Card et al. (2007)), supporting job search models (Mortensen (1977)). Decisions to leave unemployment state will be based on a problem of inter-temporal utility maximisation, and individuals will choose to stay or not unemployed depending on the most valuable available alternatives. Social Security benefits among other factors influence the labour supply behaviour. The literature on the United Kingdom data reports similar results. Meghir and Whitehouse (1997) estimate the effects of economic variables, the earnings of employed workers and the Social Security benefits, on the transition in and out of employment for older male individuals without occupational plans. Using a single competing risk model, they find that only earnings affect significantly the probability of early retiring. More recently, in their study on Spanish employed and unemployed workers, Garcìa-Pérez et al. (2013) explore the influence of financial incentives on labour transitions of older workers using an administrative data from the Spanish Social Security. They examine the determinants of both unemployed and employed workers on job search and retirement decisions. A multi-spell multi-state competing risks model with an inclusion of unobserved heterogeneity is applied to study the labour supply patterns of workers. They find a significant influence of financial incentives, that is the amount of disposable income and the amount of pension rights (i.e. pension and unemployment benefits), on individual's decisions. Pension benefits are important predictors in the transition from employment to unemployment, while unemployment benefits affect the timing between unemployment and retirement.

Therefore, the low labour market participation of older people can be the consequence of employers reluctance to hire or keep in employment older workers. Older workers may be pushed out of the labour force only on the criterion of their age. The US literature suggests a significant impact of age discrimination on employment. These studies find that older workers have problems in finding jobs and they are subject to negative stereotypes such as being less productive, overpaid, less motivated, or in bad health which result in a disadvantageous position on labour market compared to their younger counterparts. Using US data, Neumark and Stock (1999) show that the anti-age discrimination legislation, the Age Discrimination in Employment Act adopted in 1968 which purports to protect employees aged 40 and over against age discrimination in firms of twenty employees or above, has a positive effect on employment and participation rates of older workers. To identify the pure effects of anti-age discrimination laws from aggregate changes on employment, Neumark and Stock (1999) use the fact that some states had implemented the anti-age discrimination laws before the Act being voted. They find that employment rates of protected workers aged 60 and above have significantly increased by 6 percentage points and less for workers under 60 years of age (0.8 percentage points). Using a similar approach with data from the Current Population Survey between 1964 to 1967, Adams (2004) confirms Neumark and Stock's (1999) conclusions. The anti-age discrimination legislation has boosted employment of older individuals by 5.6 percentage points in the US. He also finds that the laws reduce the probability of retirement among older workers. There is evidence that anti-age discrimination legislation succeeds to increase employment rates of protected workers at cost of a decrease of those ones of unprotected workers.

3. A Brief Overview of the British Labour Market Institutions

One of the major factors influencing the labour market for older workers is the process of leaving the labour force to retire. The low participation of older persons in employment depends on labour market policies implemented in the country. This section provides some institutional background on the Social Security system in Great Britain.

The British social insurance system, one of the lowest pension payments among European countries, is qualified as "liberal". The principle is to ensure a minimum state pension, and encourage workers taking out to private pension provision. The state retirement age is fixed at 65 years for men and at 60 for women until 2010[1], and pension benefits are not available before this age. Workers have an incentive to take out given that the state pension replacement rate is low, about 35% (before the 2007 policy change). Measures such as early retirement are not possible through the public pension system[2]. The British pension system is organized into three pillars. The first tier, the Basic State Pension is a public mandatory flat-rate based on pay-as-you-go basic state pension.

[1]The retirement age was raised by six months every year from 2010 to reach 65 years in 2020
[2]You will find more details on UK pension system in Blake (2003)

The Basic State Pension is available once the state retirement age is reached and can be received while still in employment, the amount depends on the number of contributions that is at least 44 years for men and 39 for women prior to 2010.

From April 2010 onwards (i.e. the implementation of the Pension Act 2007), the number of contributions years required to full rate basic pension decreased and individuals need 30 qualifying years to receive the full Basic State Pension. To encourage activity beyond the legal retirement age, the amount of Basic State Pension can be increased if retirement is deferred, and a pro-rata approach is applied if the number of contributions required is not satisfied. The low level of flat-rate income[3](the Basic State Pension has always been below the poverty line) allows individuals who receive only the basic pension to be eligible for additional income-tested benefits. The State Second Pension is an earnings-related income and low earners, disabled people, and some individuals with caring responsibilities are eligible for this pension. In addition to these pension incomes, individuals who have left the labour force before the state pension age are also eligible for this pension. Income Support benefits is one of them, and is available for individuals who have been unemployed for at least one year and aged 60 and over. Older unemployed people are exempted from actively seeking employment, but they are not considered as retired. Workers disabled or with a long-term sick are entitled to an incapacity benefit. They have to qualified to the basis of certificates.

Additional to the State schemes, occupational schemes; personal or stakeholder plans both provided by financial companies constituted the second and third pillars. Workers are encouraged to contract-out to the private sector and personal savings by tax relief and subsidies. Occupational schemes are the most important private pension plans which cover more than two third of employees. These provide pensions by employers and two categories of occupational schemes exist, Defined Benefit and Defined Contribution pension schemes. The amount of pension provided by Defined Benefit schemes, which cover 80 % of employees, at retirement age depends on length of working life and on the wage level at the end of the career. On the other hand, the amount of pension provided by Defined Contribution schemes depends on contributions made and on the return on the investment. A worker may also make contributions under an arrangement concluded with a provider such as with an insurance company. Contributions are invested during an individual's professional career, and then they are used to buy a pension at retirement. Tax advantages, similar to those existing for occupational schemes, are applied.

Regarding unemployment insurance benefits, there are two forms of benefits which can be claimed for individuals under age of SPA, conditional on previous national insurance contributions. Contribution-based Job

[3]The full basis state pension for a single person is 90.70 per week in 2008 which is equivalent of 14% of the average earnings

Seekers Allowance (JSA-C) is conditional on actively seeking employment and on number of national insurance contributions years. JSA-C is a flat-rate benefit depending on claimant's age and can be paid up to six months. The unemployment benefit can set to 50% of the prevailing minimum wage or 50% of average last-earned wage. However, income-based JSA (JSA-I) is the second type of unemployment benefit which can be claimed by unemployed workers without any conditions on previous national insurance contributions. It is a flat-rate, means-tested benefit, whose amount depends on claimant's age and on household composition. JSA-I is paid as long as the claimant meets the eligibility requirements, or when the six-month period of eligibility for JSA-C comes to an end.

4. Unemployment Duration and the Longitudinal Labour Force Survey

In this section, we examine the time spent in unemployment for older workers. For that, we study the hazard of leaving unemployment to employment after the age of 50. We do not study the transition from unemployment to inactivity because we are interested in explaining the re-employment rate of older workers after an unemployment spell.

We address the questions of unemployment transitions of older workers using the Longitudinal Labour Force Survey (LLFS) for the period 1994 to 2009. The LLFS is a rotating panel dataset representative of the UK population. Individuals are followed over five consecutive quarters. The LLFS provides information on an individual's labour market status, which allow us to construct flows of workers between three labour market states according to the International Labour Office definitions (ILO): Employment, Unemployment and Inactivity. We can observe the labour force state at each quarter and when therefore workers experience a transition from unemployment to employment. Some of individuals remain unemployed throughout the time period. To assess the probability of leaving unemployment after age 50, we select individuals who are unemployed in period t (i.e quarter t), and could potentially leave unemployment to employment in period $t + 1$. The LLFS contains information on individual demographics such as age, gender, marital status, and information on the previous position in the labour market before job search. The period before 1994 is not considered since individual information such as marital status are only available from Spring 1994. In the same way, we cannot go further back in time, primarily, because information on the last employment are not available; secondly, because occupation classifications have changed which leads to no exact correspondence between waves.

The main advantage of the LLFS is its large number size which allows one to have a larger sample size of unemployed older workers and significant effects, contrary to other datasets such as the longitudinal survey, the British Household Panel Survey (BHPS), which provides few significant effects may be due to the small sample size. An disadvantage is it small time period but it is not important in our case as the study of unemployment spells is generally measured in months, possibly years, contrary to the analyse of employment duration which is in several years.

Unemployment duration is measured in months. The spell of unemployment is computed using quarterly information on the labour market of individuals as in Bover et al. (2002). Individuals are asked each quarter 'How long have you been looking for a job?'. We use the initial information to determine unemployment spell, and add three months for the subsequent quarters. The end of the unemployment spell is determined using the answer of the question 'How long have you been in the current job?'. We check the relevance of the unemployment duration variable with the duration unemployment reported in the survey. Individuals are also asked the date at which they left their last employment. However, we choose to not using information from the question relative to the last employment since it leads to inconsistency. The questionnaire provides in each quarter information on unemployment insurance benefits and other types of benefits such as sickness or disability benefits, or income support benefit. Unemployment benefit duration is not included in our estimations since this variable is missing for some waves of the survey.

The sample is composed by 2,090 individuals aged 50 and over, who are unemployed at the time of the survey or who become so. Spells which are not completed, i.e. spells where there is no event or transition from unemployment to inactivity, are considered as right-censored. 796 of the sample were reemployed, and 1,294 remained unemployed or became inactive. Table 1 provides descriptive statistics of unemployed workers in the sample. The right-hand side of Table 1 gives mean duration in unemployment. The mean unemployment duration is around 14 months for unemployed workers. We note that male unemployed have longer unemployment spells than the female ones. This figure is particularly large among workers with low qualifications and skilled. Transition out of unemployment is also strongly related to age. We observe that duration in unemployment is particular high for workers aged between 55 and 59. Specifically, of the 2,090 unemployed, only 35% (i.e. 280 workers) of unemployed aged between 55 and 59 are re-employed, whereas the share is 50% (i.e. 395 workers) for those aged between 50 and 54. In the next section, we examine how personal and labour market characteristics influence unemployment duration of spells.

5. Modeling the Probability of Leaving Unemployment: A Survival Approach

A discrete-time competing risks model is employed to model the transition from unemployment to other labour market states: A worker can remain unemployed, become employed, retired or economically inactive including disability, sick and family care. We assume that retirement decision is an absorbing state: the worker cannot reintegrate the labour force once retired. In the same way, we use a single-spell model since the objective of this paper is to compare the chance of re-employment between different age groups. We only examine the unemployment spell length until the first exit out of unemployment is observed, re-entry is not modeled.

Transitions from the British Household Panel Survey (BHPS), a smaller longitudinal survey of private British households, suggest that retirement can be considered as an absorbing state. Permanent retirement from the labour force is a process observed for the majority of individuals. Evidence from the BHPS indicates that 76 per cent of individuals who retired were still in retirement fives waves later. More men tend to leave definitively the labour force than women: more than 80 per cent of men remain in retirement, while 65 per cent of women are. Similarly, 70 per cent of people who are economically inactive (i.e. other than retirement status) are still in this state or move into retirement five years after they first leave employment for economic inactivity.

Competing risks models analyze the time until an event occurs, and compare this time with time until an other event is observed. This approach is preferred to single duration model because leaving unemployment may be the result of different reasons. Transition into a specific exit may be influenced by various factors, which may influence differently the exit to another state. By distinguishing exits, we can assess the impact of each covariate on different exits, whilst avoiding potential aggregation bias, and enhances understanding of seniors'unemployment. We use an independent competing risks model because we are principally interested by the effects of covariates on exits. However, independent competing risks model assumes that the distinct destination exits are independent and mutually exclusive from each other. Nonetheless, alternative specifications show that we cannot reject the hypothesis of independence of destination exits (see Appendix Subsections 8.1 and 8.2.2).

Unemployment durations are analyzed as a discrete-time competing risks model as the model is more appropriate when data are collected on a yearly basis, even though the underlying process out of unemployment is assumed to be continuous. "The data are not intrinsically discrete, but they are grouped into intervals of unit length" (Jenkins, 2005, p.97). The idea is to divide the time spent in unemployment into time interval, and to study whether individuals have left or not unemployment state in each time interval. The unit of the time intervals in our analysis is a year. The basic idea of the hazard rate models is to analyze whether there is a transition at each time interval rather than the duration spent in a state.

A discrete-time competing risks model is used to study unemployment duration T^s_{ij} which is the time spent in unemployment for the individual i, for $i = 1, ..., N$, in the s^{th} spell (i.e. unit of spell is a year), for $s = 1, 2, 3, ..., S_i$ of state j before that an event occurs or i remains in unemployment. j is the initial labour force status of the individual, that is being unemployed. T^s_{ij} is a discrete random variable divided into time intervals I_t, with $t \in \{1, ..., T^s_{ij}\}$. $T^s_{ij} = t$ if an individual leaves unemployment state and $T^s_{ij} > t$ if an individual remains unemployed at the end of interval I_t. A worker may leave his current unemployment either for employment, retirement or other sates of economic inactivity. The spell is complete in this case. A worker who does not experience an event during the sample period or who reaches the legal age of retirement is defined as right-censored. The length of unemployment is examined by estimating the duration after 50.

The specific-destination discrete hazard rate $h^s_{ijk}(t)$ for the individual i is the probability of making transition from the j state (i.e. unemployment) to the state k (employment, economically inactivity) at his s^{th} spell for $k \neq j$, conditional on being unemployed at the beginning of the interval I_t and on observed characteristics ($X_{ijk}(t)$) and unobserved characteristics (ϵ_{ij}).

$$h^s_{ijk}(t) = Prob(t \mid X_{ijk}(t), v_{ijk}) = Prob(T^s_{ij} = t, \lambda^s_{ij} = 1 \mid T^s_{ij} \geq t, X_{ijk}(t), \epsilon_{ij}) \tag{1}$$

which is given by:

$$h^s_{ijk}(t) = \frac{f^s_{ijk}(t)}{S(t-1)} \tag{2}$$

where $T^s_{ij} = min\{T^*_{ij}, C^*_{ij}\}$ with T^*_{ij} a latent failure time, and C^*_{ij} a latent censoring time for the individual i. λ^s_{ijk} is dummy variable equals one if the event $k = 1, 2, 3$ (i.e. the destinations are employment, retirement or other states out of labour force) and 0 otherwise. $f^s_{ijk}(t)$ is the destination specific density function at time t, and $S(t-1)$ is the survival function in unemployment until the beginning of the interval t.

The probability that the individual i does not leave unemployment at the s^{th} spell, conditional that he was unemployed at the beginning of interval I_t is given by the survivor function S_{ijk}.

$$S_{ijk} = Prob(T^s_{ij} > t) = \prod_{j=1}^{t}(1 - h^s_{ijk}) \tag{3}$$

The likelihood contribution of the individual i with a completed spell with a discrete-time density function (i.e. the probability that an event is observed between t_{-1} and t) is :

$$\begin{aligned} f_{ijk} &= Prob(t-1 < T^s_{ij} \leq t) \\ &= S_{ijk}(t-1) - S_{ijk}(t) \\ &= \left[\frac{h^s_{ijk}}{1-h^s_{ijk}} \prod_{j=1}^{t}(1 - h^s_{ijk})\right] \end{aligned} \tag{4}$$

The overall contribution to the likelihood L is the product of the individual likelihoods L_i for individual i=1,...,N and given by :

$$L = \prod_{i=1}^{N} \left[Prob(t-1 < T_{ij}^{s} \leq t)\right]^{c_i} \left[Prob(T_{ij}^{s} > t)\right]^{1-c_i} \tag{5}$$

$$= \prod_{i=1}^{N} \left[\left(\frac{h_{ijk}^{s}}{1-h_{ijk}^{s}} \right)^{c_i} \prod_{j=1}^{t} (1-h_{ijk}^{s}) \right] \tag{6}$$

where c_i is defined as:

$$c_i = \begin{cases} 1 \quad \text{if} \quad \text{the spell is completed} \\ 0 \quad \text{si} \quad \text{the spell is censored} \end{cases} \tag{7}$$

The log likelihood $log\ L$ is :

$$logL = \sum_{i=1}^{N} c_i \log\left(\frac{h_{ijk}^{s}}{1-h_{ijk}^{s}} \right) + \sum_{i=1}^{N} \sum_{j=1}^{t} \log(1-h_{ijk}^{s}) \tag{8}$$

However, the log likelihood given in Equation (8) cannot be maximized directly, Allison (1992), Jenkins (1995) and Jenkins (2005) propose to rewrite Equation (8) as a function of binary dependent variable y_{ijk} for an easy estimation :

$$logL = \sum_{i=1}^{N} \sum_{j=1}^{t} y_{ijk} \log\left(\frac{h_{ijk}^{s}}{1-h_{ijk}^{s}} \right) + \sum_{i=1}^{N} \sum_{j=1}^{t} \log(1-h_{ijk}^{s}) \tag{9}$$

$$= \sum_{i=1}^{N} \sum_{j=1}^{t} \left[y_{ijk} log\ h_{ijk}^{s} + (1-y_{ijk}) log\ (1-h_{ijk}^{s}) \right] \tag{10}$$

where y_{ijk} is defined as:

$$y_{ijk} = \begin{cases} 1 \quad \text{if} \quad \text{the individual leaves unemployment state during the time interval [t-1,t]} \\ 0 \quad \text{if} \quad \text{the individual remains in unemployment during the time interval [t-1,t]} \end{cases} \tag{11}$$

With this trick, the log likelihood function (Equation (10)) can be estimated by a binary models such as a logit model, and the other exit destinations are considered as censored. This requires a re-organization of the data into individual-year format (see Appendix Section A.2 for more details).

To estimate empirically the models, other assumptions about the state transitions between time intervals and the functional form for the destination-specific continuous hazard are required. Indeed, in a continuous model with several exits, the log-likelihood is the sum of the log-likelihoods for each of the destination-specific models, and each sub-contribution depends only on the parameters specific to that destination. Estimating a competing risks model with multiple destinations in a continuous case is easy because it is equivalent to estimate a single-destination model separately, one for each destination. Contrary to the continuous case, the separability property does not hold for the discrete-time censored interval case because more than one latent event is observed in each time interval, and the observed exit corresponds to the minimum of the latent survival times. “Put another way, when constructing the likelihood and considering the probability of observing an exit to a specific destination in a given interval, we have to take account of the fact that, not only was there an exit to that destination, but also that exit occurred before an exit to the other potential destinations” (Jenkins, 2005, p. 97).

One way to model discrete-time competing risks is to assume that the destination-specific density functions (or hazard rates) are constant within time interval, and may vary between intervals. An alternative assumption is that the transition between states occurs at the boundaries of the time intervals. Following Narendranathan and Stewart (1993) and Jenkins (2005), we assume that the transition occurs at the end of the time interval. As a result, the log-likelihood for competing risks is the same as for continuous case, and it can be estimated by a single-risk model. The destination specific hazards can be estimated separately with a logit model and the other destinations are considered as censored. One restriction is that the model assumes the independence between competing risks, so that correlation between unobserved explanatory variables does not affect each exit. In other words, an individual can leave unemployment to one state, independently of the others. As in Meyer (1990), the discrete-time hazard specification $h^s_{ijk}(t)$ is assumed to take the complementary log-log form (i.e. the underlying continuous time hazard rate is a proportional hazard model).

$$h^s_{ijk}(t) = 1 - exp\left[-exp\left(\gamma_{jk} + \beta^{'}_{jk}x_{ijk}(t)\right)\right] \tag{12}$$

where $\gamma_{jk}(t)$ is the baseline hazard function, $x_{ijk}(t)$ is a vector of explanatory variables.

Another important point in hazard models concerns the unobserved heterogeneity, especially when the exit out of unemployment is analyzed (Addio and Rosholm (2002), Farber (1994)). Unobserved heterogeneity corresponds to unmeasured characteristics which are important to explain variability in the hazard rate between individuals, but which are not included or are not measurable in the model because they are not available in our dataset. Not accounting for unobserved heterogeneity when unmeasured characteristics are correlated with the explanatory variables included in our model can introduce bias in the duration dependence and in the regressors coefficient estimates. To illustrate how the baseline hazard rate can be affected by unobserved heterogeneity, suppose that the sample is composed by two types of workers with hazards constant over time, but one of them has a higher hazard than the other. If we cannot distinguish these two types of workers, the estimated hazard will be a mixture of these two hazard rates. As time goes by, workers with higher hazards will leave the sample at faster rate, leading to a sample composed of workers with a low ϵ_{ij}. The aggregated hazard rate will be decreasing over time. Accounting for unobserved heterogeneity when unmeasured characteristics such as ability, work effort or motivation can affect the worker decision of leaving his current work position is important. On the other hand, literature explains that accounting for unobserved heterogeneity is not necessary. Meyer (1990) shows that unobserved heterogeneity will not introduce bias in the estimates when a flexible specification for duration dependence is used. Moreover, Narendranathan and Stewart (1993) point out that a misspecification of unobserved heterogeneity may bias the estimates. The standard approach to deal with unobserved heterogeneity is to include a random variable, specific to the individual and fixed over time and with a given distribution. The hazard rate can be rewritten as:

$$h^s_{ijk}(t) = 1 - exp\left[-exp\left(\gamma_{jk} + \beta'_{jk}x_{ijk}(t) + \epsilon_{ij}\right)\right] \tag{13}$$

where ϵ_{ij} are the unobserved characteristics distributed according to a Gamma or a Normal distribution. The presence of unobserved heterogeneity is tested under the null hypothesis that the variance equals zero. Under the null hypothesis, the unobserved heterogeneity is not important and the model can be estimated without including heterogeneity. Unobserved heterogeneity can also be treated in a nonparametric way. Heckman and Singer (1984) assume that there are a number of different individuals or mass points, and each mass point can be assigned to a probability. ϵ_{ij} is assumed to follow a discrete distribution, ϵ_{ij} is divided into M mass points, $m = 1, ..., M$ with a probability $Pr(\epsilon_{mj})$. Unobserved heterogeneity is incorporated in the hazard function by the intercepts, m_{type}, which are different for the different type of individuals.

$$h^s_{ijk,type}(t) = 1 - exp\left[-exp\left(\gamma_{jk} + \beta'_{jk}x_{ijk}(t) + m_{type}\right)\right] \tag{14}$$

The likelihood function will be a mixture of contributions of different types of individuals, weighted by the probabilities associated to the mass points. We choose to not include a nonparametric unobserved heterogeneity due to the difficulties encountered in the estimation. Meyer (1990) claims that the computation difficulties encountered are the result of the parametric assumption of the baseline hazard form imposed in the Heckman and Singer (1984) approach. Additionally, Narendranathan and Stewart (1993) add that bias in the Heckman and Singer (1984) paper are due to parametric form of the duration dependence. Several specification for individual unobserved heterogeneity distribution can be considered without a substantial on the estimates parameters. Meyer (1990) shows that the choice of distribution assumed for unobserved heterogeneity is non important when a flexible specification for duration dependence is used. "When the baseline hazard is non parametrically estimated, the choice of heterogeneity distribution may be unimportant" (Meyer, 1990, p.771). In their paper, Jenkins and Garcìa-Serrano (2004) justify the fact of not including unobserved heterogeneity due to the long estimation routines of mixture models needed to converge[4].

$\gamma_{jk}(t)$ in Equation 13 is the baseline hazard function. It represents the duration dependence of the hazard rate, that is how hazard rate evolves over time elapsed in the unemployment state given that all explanatory variables are held constant. We consider alternative specifications for the functional form for the baseline hazard function, a parametric specification, i.e. the logarithm of the baseline hazard, and a nonparametric specification. The parametric specification of baseline hazard function imposes strong restrictions on the form of the hazard rate, while the nonparametric specification has the advantage to introduce more flexibility for the duration dependence path and avoid misspecification. The baseline function is modeled using duration dummies. The duration dependence is assumed to be constant within time intervals, but it can vary between intervals. Duration dependence is specified in a flexible way by introducing a dummy variable for monthly duration of unemployment. We create for that 22 interval-specific dummy variables, one for each month at risk. However, time intervals are clustered to ensure that events occurring within each of the time intervals. Thus, a variable labelled $Interval_{t-t+1}$ is equal to one if the unemployment duration corresponds to a spell of t and t+1 months, and 0 otherwise. The advantage to treat duration dependence with a flexible functional form is to reduce the effects of unobserved heterogeneity on duration dependence and covariates estimates. Estimates are more robust with flexible duration dependence specification (Dolton and van der Klaauw (1995), Narendranathan and Stewart (1993)).

6. The Effect of Age, Human Capital and Economic Incentives on Re-employment

The reference individual for the estimation is a married male (or female) who lives in Scotland, without qualifications and who was previous in an unskilled position before unemployment, and who does not receive unemployment or disability benefits.

We present here the estimates from the estimation of a discrete time proportional hazard model which allows for unobserved heterogeneity for transitions from unemployment to employment. Both parametric and nonparametric specifications have been used, but only the nonparametric estimates will be presented. The effects of covariates are similar across specifications. Furthermore, we do not present estimated results for other exits (i.e. Retirement, Inactivity and Other states of inactivity) in the remainder of the paper because the main interest of our study is to analyse reasons individuals have less employment opportunities when they grow older. Table 2 shows the estimated results of exiting from unemployment to employment by gender, with a nonparametric

[4]For example, it takes more than three weeks to have a converge of the maximum likelihood estimator. Moreover, we encounter convergence issues with a Gamma distribution caused by the value of the log of variance, $Log\ \sigma_{\epsilon}^{2}$, around -10. Jenkins (2005) claims that the convergence problems result from the value of variance close to zero, while the model is programmed with a gamma variance constrained to be positive

baseline dependence specification. We focus mainly on the effects of three variables widely used in job search models: Age, human capital and economic incentives. We do not report estimates of other controls which include household composition characteristics, race, heath status, previous occupations and firms characteristics, individual's region of residence, labour market conditions measured by regional unemployment rates, calendar year dummies and a piecewise constant baseline hazard.

6.1. Age and Long-term Unemployment

Age is included in the model because we are interested in employment opportunities which occur late in life, and in elderly employment barriers issues. Starting with age which is considered as continuous variable, the estimates indicate that the hazard of leaving unemployment declines with age among older males (see Table 2 columns (1) and (2)). Older workers have lower hazards than 'younger' workers. For instance, an unemployed male aged 51 will have 7% lower probability to exit unemployment than someone aged 50, while the probability to leave unemployment to employment is not affected by age for females.

However, age terms are significant for both genders when the analysis is undertaken between 'younger' and 'older' groups of workers. Age is grouped into three categories: 50-54 years old, 55-59 years old, and 60 and over for males. Columns (2) and (4) of Table 2 report estimates of age terms. We observe that the coefficients associated with age bands are statistically negative relative to the 50-54 years old for both genders. Among males, unemployed workers aged between 55 and 59 will have 25% lower chance of leaving unemployment to employment than those in the 50-54 age group. This figure is more pronounced for the oldest group: Individuals aged between 60 and over have more than 47% lower hazard rate of leaving unemployment relative to their counterparts aged less than 55. 'Younger' unemployed workers have a higher chance of getting back to employment. Females aged 55 and over have 33% lower probability to find a new employment than females under the age of 55.

Age is an important factor for unemployment duration, and it could explain in part the difficulties encountered by older workers to find a new employment since they have the lowest exit rates from unemployment to employment. The low probability of finding an employment could be attributable to skill obsolescence, and the fact that the elderly may be less likely to adapt new technologies. Yet, state of health which reflects decline of work abilities is not statistically significant, regardless of gender. Health status is not a key factor which could explain the poor prospects of re-employment later in life. One explanation could be attributable to age discrimination, or at least, to discriminatory behaviours. Age discrimination and stereotypical beliefs from employers could also explain the low transition rate from unemployment to employment. Employers may be reluctant to hire senior workers because they can be perceived as less productive, in poor health and less able to learn than their younger ones. On the other hand, the low hazard rate could reflect individual's preferences to remain unemployed instead of undertaking a new job. Seniors are more willing to remain unemployed since individual's preferences for non-employment activities increase in later years (life-cycle allocation of time).

6.2. Human Capital and Job Opportunities

Turning to human capital characteristics, several studies have stressed the positive role of human capital characteristics on unemployment incidence (Mincer (1991b), Mincer (1991a) and Nickell (1979)). In this literature, more human capital reduces unemployment durations and improves the re-employment rate of job seekers. Since human capital can be distinguished between general human capital and specific human capital, we only investigate how general human capital change re-employment probability. This later can be approximated by educational level and reflects the 'general' skills accumulated through education and job experience, and it could be transferable between firms, in contrary to specific human capital. In our case, general human capital is captured by four dummy variables: A level (or equivalent), Higher education or college degree, GCSE-O level and below, and no qualifications.

As would be expected, education level significantly affects the chance of leaving unemployment and the effect is more important among females. Females with higher education level or with a GCSE-O level have higher and significant chance of returning to work compared to those with no qualifications. The effect of education level is significantly greater for females with high educational attainment: the probability to return to work increases by more than 50% for females having a college degree, by 60% for females with a GCSE-O level, by 30% for males with a GCSE-O, compared to those with no qualifications. Education level may be interpreted as a signal of high productivity of individuals, which leads employers to hire unemployed workers with higher education level, expecting a higher productivity.

6.3. The Role of Economic Incentives on Re-employment

Finally, we investigate how economic incentives could affect the unemployment hazard rate. The existing literature on unemployment duration finds a correlation between unemployment incidence and social benefits (Jenkins and Garcìa-Serrano (2004), Meyer (1990)). Effects of social benefits could explain, in part, the long period of unemployment that are facing older people. To deal with this question, we include in the regressions two dummies to control for these potential disincentive effects: Unemployment insurance benefits and sickness or disability benefits.

With respect with unemployment insurance benefits, results in Table 2 indicate that the effect of unemployment insurance benefits is not statistically significant. Receiving unemployment benefits seems not to affect the re-employment rates on average, regardless of gender. Our findings are in accordance with Jenkins and Garcìa-Serrano (2004) who show for Spain that unemployment benefit has small effect on re-employment hazards, and no significant effect for men in long-term unemployment. Similarly, Arulampalam and Stewart (1995) find that unemployment benefit has no effect for men aged 45-64 in Britain. Given that unemployment duration in our sample is, on average, high (i.e. 14 months on average) this could explain why unemployment benefit has negligible disincentive effects on re-employment probability for older workers. However, results support the idea that social benefits increase unemployment spell length. Coefficients associated to disability benefits are significantly negative which is consistent with job search theory. Receiving sickness or disability benefits lower the probability of leaving unemployment. In other words, social benefits other than unemployment insurance benefits affect negatively the chance of re-employment among older males, but the effects are not statistically significant among unemployed females. Social benefits create strong work disincentive effects, which could discourage workers to search for a work at the end of their professional careers.

7. Explaining the Differences Between Average Unemployment Duration of 'Younger' and 'Older'

The descriptive statistics reveal differences in average unemployment duration between age groups, regardless of gender (see Table 1). Elderly jobless workers have longer length of unemployment spells than the younger ones, in the order of 2.8 months for the 55-59 age group, and 3 months for the 60-64 age group. This confirms that there exists an age gap in unemployment duration. The next step is to decompose the age difference of duration of unemployment. To examine differences in duration of unemployment among age groups, we apply the Oaxaca approach developed by Bazen et al. (2017) for nonlinear models. The decomposition can be straightforward if we use a continuous time Weibull specification. A continuous time Weibull specification can be used in our case because discrete time models with the parametric baseline hazard specification are equivalent to continuous time Weibull models (see Jenkins (2005)). And as unobserved heterogeneity is not significant to explain the duration of unemployment, the effects of unobserved heterogeneity on duration dependence and covariates estimates are marginal, using a parametric baseline hazard specification instead of nonparametric specification is no longer important. Therefore, we use a continuous time Weibull model to decompose the difference in unemployment duration between age groups of unemployed workers.

The usual decomposition of the mean (Oaxaca (1973), Blinder (1973)) is widely used to identify the contribution of observed characteristics and of unobserved characteristics such as racial or gender discrimination in differences of outcomes between groups in linear models. A number of approaches have been developed to deal with decomposition nonlinear models (see Fairlie (2005), Powers and Myeong-Su (2009)). However, here we follow Bazen et al. (2017) to decompose the age gap between groups of unemployed workers. The Oaxaca type decomposition for duration models is as follows:

$$O(\bar{x}_o) - Y(\bar{x}_y) = \bar{\Gamma}(\hat{\alpha}_o)exp(\bar{x}_o'\hat{\beta}_o) - \bar{\Gamma}(\hat{\alpha}_y)exp(\bar{x}_y'\hat{\beta}_y) \quad (15)$$

$$with\ \bar{\Gamma}(\hat{\alpha}_i) \equiv \Gamma\left(\frac{1+\alpha_i}{\alpha_i}\right)\ ,\ i = o, y \tag{16}$$

and O refers to older group that is 55-59 age group and Y refers to younger one, i.e. the 50-54 age group, $\bar{\Gamma}$ is the gamma function, $\hat{\alpha}$ is the estimated baseline hazard function, $\bar{x}$ is the vector of means of explanatory variables for the two groups, and $\hat{\beta}$ are the parameters from the hazard models.

To disentangle the age gap between groups of unemployed individuals, we estimate two hazard models for time spent in unemployment separately for individuals aged between 50 and 54 years, and for those aged between 55 and 59 years. We assume that the hazard rate takes a Weibull form. We choose to assess the age gap in time spent in unemployment between individuals in the 50-54 and 55-60 age groups because individuals are close in terms of characteristics related to job search, such as attachment to employment, and it makes the analysis more consistent than the decomposition with workers in the 60-64 age group, workers who are close to the state age retirement and therefore perhaps more encouraged to early retirement. The detailed and aggregate decomposition results of the gap in mean duration of transition toward employment are presented in Tables 3 and 4. The average characteristics of the older age group are used in the counterfactual for the decomposition of the estimated expected duration. The unemployment duration differential decomposed by the Oaxaca method can be rewritten as follows:

$$O(\bar{x}_o) - Y(\bar{x}_y) = \left[\bar{\Gamma}(\hat{\alpha}_o)exp(\bar{x}_o'\hat{\beta}_o) - \bar{\Gamma}(\hat{\alpha}_y)exp(\bar{x}_o'\hat{\beta}_y)\right] + \left[\bar{\Gamma}(\hat{\alpha}_y)exp(\bar{x}_y'\hat{\beta}_y) - \bar{\Gamma}(\hat{\alpha}_y)exp(\bar{x}_o'\hat{\beta}_y)\right] \tag{17}$$

The first term represents the differences in unemployment duration due to the estimated coefficients. This unexplained part of age gap in unemployment spell length captures unobserved characteristics such as individual preferences, but it can also be interpreted as age discrimination. It allows us to know the predicted length of an unemployment spell of older unemployed when facing same conditions as a younger unemployed. The second term captures the differences in means due to observed characteristics between age groups.

The decomposition is also undertaken with the average characteristics of the younger group (see bottom of Table 4), and the results are qualitatively the same. The overall gap is 16.9 months and it can be decomposed into two counterfactual gaps: -2.49 (or -15%) of the mean duration of leaving unemployment to employment is attributed to differences in mean of observed characteristics between 'younger' and 'older' unemployed workers. The rest of the gap (i.e. -115%) is due to differences in the estimated coefficients. The unexplained part largely accounts for the unemployment rate gap between 'older' and 'younger' workers. There is evidence of differences of treatment in the labour market since the unemployment duration would be lower if 'older' unemployed were given the 'younger' coefficients. Results indicate that the duration of unemployment would be lower for individuals in the 55-59 age group if older unemployed workers will be given coefficients of younger workers (see Table 4). The unemployment duration would be 21.6 months if workers aged between 55 and 59 would be treated in the same way as the younger workers instead of 41 months. The decomposition is also undertaken separately for males and females, and the results provide similar conclusions. Simulations show that males and females with characteristics of 'younger' groups will experience lower unemployment spell length. The findings indicate age differences in re-employment between younger and older groups of workers, which is consistent with discriminatory attitudes against older workers. Older workers in unemployment could be discriminated against in the labour market because of their age.

The decomposition shows that older workers could be discriminated on the labour market since their unemployment duration would be lower if older workers will be treated as younger workers. The next step is to assess whether the difference in returns between the two age groups are significant. We test the presence of discrimination of a null hypothesis of equality of parameters of the two groups with a Chow test. The Chow test rejects the null hypothesis of equality of parameters. The coefficients are significantly different across age groups, which brings us to think that discrimination or at least discriminatory acts exist between our two age groups. Chow tests have also been used to identify possible age differences among gender. In both cases, the test is rejected implying presence of significant differences between age, whatever the gender of workers. The results depicted in Table 4 should be interpreted with care due to the strong correlation between age discrimination, and a higher reservation wage among older workers, for example. Prejudicial attitudes could explain the difference gap in time spent in unemployment and probability of being re-employed, however we are not able to conclude whether the duration of unemployment is only due solely to discrimination against older workers because of their age.

8. Robustness Analysis

In this section, we present some robustness checks that address particular points concerning the definition of destination exits, the definition of time intervals of the duration dependence and the specification of the model. We considered alternative specifications to check the sensitivity of the parameter estimates. The shape of the duration dependence is treated with a parametric (i.e. log duration of spells) and a flexible specifications. We also specify the hazard rate with alternative functional form: a logit, a probit and a multinomial logit model.

8.1. Alternative Definitions for Destination Exits

Table A3 provides the results of test specifications. In first step, we test whether alternative exits, unemployment and inactivity, might be distinguished from the pooled specification. We run a series of LR tests to check whether the states have to be separated or combined into a single category. The null hypothesis that the coefficients of the two candidates for pooling are identical is rejected for each alternative. Unemployment and inactivity are significantly different destination states. The competing risks model seems to be appropriate given the rejection of tests. Another series of LR tests are used to determine whether the right functional form of the baseline hazard is a parametric or a nonparametric specification. The LR tests show that the null hypothesis cannot be accepted for any alternatives. The data support a nonparametric baseline hazard function. In addition, the $log\ likelihood$ is always higher in value for the nonparametric baseline hazard regressions which means that flexible specification fits the data better.

8.2. Alternative Specification for Hazard Rate

8.2.1. A Logit Specification

Estimates may depend on models used. To check the sensibility of our results, alternative specifications for the functional form of the hazard rate are considered to ensure that the results do not depend on models used. Firstly, we re-estimate the models with a logit specification. Unobserved heterogeneity is included, and it is assumed to follow a Normal distribution with a zero mean and a variance σ_ϵ^2. The destination specific hazard becomes:

$$h_{ijk}^{s}(t) = \frac{1}{1 + exp\left(-\gamma_{jk} - \beta_{jk}^{'} x_{ijk}(t) - \epsilon_{ij}\right)} \tag{18}$$

The estimated coefficients (i.e $\hat{\beta}$) are presented in Table A1 with a nonparametric baseline hazard. The results are substantial similar to those with a complementary log-log specification, but the interpretation of coefficients is different.[5] The exponentiated coefficients (i.e $exp(\hat{\beta})$) are interpreted as odds ratios for the logit models, and as relative risks for the complementary log-log models. For instance, receiving sickness or disability benefit has a negative effect on exit into employment. The odds of leaving unemployment to employment is 0.38 times lower for males with sickness/disability right relative to those without right, and not significant for females. However, age is a relevant factor explaining employment decisions for both gender. Males aged between 55-59 years old have 0.74 (0.63 for females) times lower chance to be re-employed than those aged between 50-54 years old, and 0.46 for males aged between 60-64 years old.

8.2.2. A Multinomial Logit Specification

The competing risks of leaving unemployment after the age of 50 is also estimated with a multinomial logit model. The destination-specific hazard rate is assumed to take a multinomial logit form:

[5] We have also estimated the model with a probit specification. Logit and probit regression models give similar results, but estimated in logit model are around 1.7 times higher than they are in probit model. The estimation results from probit model are not presented but are available upon request.

$$h^s_{ijk}(t) = \frac{exp(\gamma_{jk}(t) + \beta'_{jk} x_{ijk}(t) + \epsilon_{ij})}{1 + \sum_{l=1}^{3} exp(\gamma_{jl}(t) + \beta'_{jl} x_{ijl}(t) + \epsilon_{ij})} \tag{19}$$

for $i = 1, ..., N$ and $j = 0, 1, 2$.

Results are reported in Table A2. As for previous model, there is three distinct exits: employment, unemployment, retirement and other states of inactivity. The unemployment state is defined as the base category (i.e. $l = 0$). Overall, the results from the multinomial logit regression are similar to those from the competing risk models. The signs and pattern are comparable across specifications. As for the other models, age matters for employment decisions. Older workers exhibit a significantly lower probability of exiting from unemployment to employment compared to younger workers. Again, male seniors have a higher probability of leaving early labour force than their female counterparts. Unemployment insurance benefit decreases the probability to leave unemployment for inactivity, while sickness or disability benefit has different effects across destination states. It decreases the log odds of being employed after the age 50 compared to those in unemployment, and it increases the log odds of being inactive after the age 50 compared to those in unemployment among males, as in competing risks models. Social benefits are used as a means to leave the labour force at older ages. These findings are in line with those of previous studies on pension system reforms (Staubli and Zweimüller (2013), Charni (2016)) which show a substitution effect between social security benefits.

One of limitations of the multinomial logit model is the independence of irrelevant alternatives (IIA). Basically, in a model with three alternatives, the IIA assumption suggests that the ratio of probabilities of two alternatives does not change if a third one is added in the model. In other words, characteristics of a third option will not affect the odds among the remaining options. The IIA assumption is tested by two means of tests. However, these specification tests are based on estimations without including unobserved heterogeneity due to the long computation time of the estimation with unobserved heterogeneity. The results of the IIA test, from the Hausman-McFadden and Small-Hsiao tests, given in Table A4 for the full sample, provide conflicting results on the violation of the IIA assumption. The Hausman-McFadden test suggests that the two alternatives can be treated independently, while the Small-Hsiao test rejects null hypothesis if we remove the first alternative, i.e employment, from the model. McFadden (1973) and Amemiya (1981) point out the fact that multinomial logit model works better when the alternatives are distinct and not substitutes for one another. The Wald and LR tests given in Table A4 reject the null hypothesis that any pair of alternatives is indistinguishable and should not be combined. Distinguish exits into employment, retirement and other state of inactivity seem to be appropriate for our data.

8.3. Alternative Definitions for Duration dependence

Similarly, sensitivity analysis have been performed for the definition of time intervals of the duration dependence. The shape of the duration dependence is treated with a parametric (i.e. log duration of spells) and a flexible specifications. We also check the sensitivity of time intervals of the duration dependence by changing the time interval, and findings remain consistent.

9. Conclusions

This paper examines the employment opportunities of older workers in Great Britain by analysing unemployment exits of those aged 50 and above. We identify that human capital characteristics significantly increase the re-employment probability of the elderly. In other way, economic incentives play a role in explaining unemployment duration by reducing the probability of being in employment at older ages and create strong work disincentive effects. Our results indicate that the chance of moving from unemployment to employment are strongly related to the age of workers. As they age, unemployed workers are less likely to return to employment. This result suggests that older workers face bad labour market opportunities, and it could explain the difficulties encountered by older workers to find a new employment. To understand the role played by the age on unemployment duration and the chances of being back into employment among older unemployed workers, an Oaxaca type decomposition is undertaken between two age groups: younger ant older age groups. Based on these simulations, we detect age differences in re-employment probability of workers. Older workers may be discriminated on the labour market since their unemployment duration would be lower if they will be treated in the same way as the younger workers. Employment opportunities do decrease for older unemployed workers, and the age explains in part this decline of employment prospects. These conclusions could explain the low employment rates observed among older workers.

These findings have important policy implications regarding the low employment and long unemployment spells that are facing older people. A better understanding of factors that influence labour market participation of workers later in life could improve their labour market position.

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Table 1: Summary Statistics: Unemployment duration by gender

	Proportion			Mean Duration		
	Full sample	**Males**	**Females**	**Full sample**	**Males**	**Females**
Demographics						
		0.66	0.34	14.3	15.96	11.1
Married	0.69	0.71	0.65	12.4	13.8	9.5
White	0.96	0.96	0.96	14.2	15.9	10.8
Age						
50-54	0.42	0.37	0.53	12.6	14	10.5
55-59	0.37	0.36	0.47	15.4	17.3	12
60+	0.21	0.27		16.5	16.5	
Highest education attainment						
College/University	0.27	0.34	0.13	14.8	15.7	10.1
A level or equivalent	0.21	0.20	0.23	11.7	13.1	9.1
Gcse/O level	0.14	0.11	0.19	11.6	13.4	9.4
No qualification	0.38	0.35	0.45	16.3	18.4	13.1
Previous Position						
Professional	0.10	0.10	0.10	11.6	12.6	9.5
Managerial	0.16	0.19	0.08	14.1	14.4	12.5
Skilled manual	0.27	0.26	0.30	14.9	16.8	11.5
Skilled non manual	0.34	0.33	0.37	13.9	16.2	10.3
Unskilled	0.13	0.12	0.15	16	18.2	12.7

Notes: Mean unemployment duration is expressed in months. Information on unemployment duration are given for censored and uncensored spells.
Source: own calculations based on LLFS, 1994-2009.

Table 2: Probability of re-employment by gender – Competing Risks Model results

	Males		**Females**	
	(1)	**(2)**	**(3)**	**(4)**
Age	-0.0696***		-0.0265	
	(0.0113)		(0.0183)	
Age_{55-59}		-0.284***		-0.411***
		(0.0989)		(0.138)
Age_{60-64}		-0.751***		
		(0.129)		
A level or equivalent	0.226	0.198	0.326	0.302
	(0.153)	(0.153)	(0.216)	(0.215)
Higher education or college degree	0.145	0.138	0.448**	0.380*
	(0.117)	(0.117)	(0.206)	(0.208)
GCSE-O level and below	0.271*	0.274*	0.479**	0.456**
	(0.159)	(0.159)	(0.189)	(0.189)
Unemployment insurance benefit	0.134	0.127	-0.171	-0.123
	(0.0940)	(0.0956)	(0.140)	(0.139)
Sickness or disability benefit	-0.935***	-0.939***	-0.391	-0.374
	(0.286)	(0.287)	(0.376)	(0.375)
Observations (indiv.-spell)	22,054	22,054	7,922	7,922
Number of individuals	1,383	1,383	707	707
LR χ^2	864.1	859.7	411.0	417.0
Prob< χ^2	0.000	0.000	0.000	0.000
log likelihood	-1960	-1962	-911.1	-907.6

Notes: In addition to variables shown, an intercept and controls for education, household composition characteristics, race, health status, previous occupational status, firm characteristics, individuals' region of residence, regional unemployment rates, and dummy for yearly baseline hazard were included in all specifications. The baseline hazard rate is nonparametric.
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: own calculations based on LLFS, 1994-2009.

Table 3: Decomposition of unemployment duration: Means and Estimates for the full sample

	Means		Difference	Estimates		Difference
	$\bar{X}^{50-54}$	$\bar{X}^{55-59}$		$\hat{\beta}^{50-54}$	$\hat{\beta}^{55-59}$	
Constant	1	1	0	-3.738	-3.092	0.646
				(0.471)	(0.556)	
A level or equivalent	0.231	0.206	0.025	0.137	0.326	-0.189
	(0.422)	(0.404)		(0.185)	(0.190)	
Higher education or College degree	0.253	0.258	-0.005	0.242	0.220	0.022
	(0.435)	(0.437)		(0.147)	(0.165)	
GCSE-O level and below	0.148	0.138	0.01	0.357	0.195	0.162
	(0.355)	(0.345)		(0.170)	(0.202)	
Married	0.671	0.694	-0.023	0.622	0.750	-0.128
	(0.470)	(0.460)		(0.119)	(0.144)	
Male	0.577	0.660	-0.083	-0.280	-0.209	0.071
	(0.494)	(0.473)		(0.121)	(0.149)	
White	0.962	0.964	-0.002	0.765	0.320	0.445
	(0.189)	(0.185)		(0.327)	(0.402)	
Managers and Senior Officials	0.168	0.144	0.024	-0.150	-0.026	0.124
	(0.374)	(0.351)		(0.213)	(0.250)	
Professional occupations	0.109	0.0944	0.014	0.324	0.121	0.203
	(0.312)	(.292)		(0.256)	(0.284)	
Associate Professional and Technical	0.090	0.094	-0.004	0.464	0.114	0.35
	(0.286)	(0.292)		(0.239)	(0.271)	
Administrative and Secretarial	0.129	0.137	-0.008	-0.208	-0.127	0.081
	(0.336)	(0.344)		(0.225)	(0.260)	
Skilled Trades Occupations	0.131	0.147	-0.016	-0.103	0.107	-0.313
	(0.337)	(0.354)		(0.217)	(0.246)	
Personal Service Occupations	0.064	0.0576	0.006	-0.003	0.452	-0.449
	(0.245)	(0 .233)		(0.286)	(0.297)	
Sales and Customer Service Occupations	0.070	0.0587	0.011	-0.290	0.0196	-0.309
	(0.255)	(0.235)		(0.258)	(0.306)	
Process, Plant and Machine Operatives	0.110	0.1394	-0.029	-0.008	0.142	0.134
	(0.313)	(0.3465)		(0.217)	(0.241)	
Unemployment Insurance Benefit	0.462	0.427	0.035	0.090	-0.008	0.081
	(0.498)	(0.494)		(0.109)	(0.120)	
Sickness or Disability Benefit	0.053	0.0564	-0.0034	-0.523	-0.735	-0.212
	(0.224)	(0.230)		(0.307)	(0.369)	
Regional Unemployment Rate	6.596	6.614	-0.018	-0.195	-0.180	-0.015
	(2.019)	(2.108)		(0.0368)	(0.0397)	

Notes: The other explanatory variables are dummies for individual's region of residence, and the baseline hazard function is given by the Weibull distribution. Standard deviations and standard error in parentheses.
Source: own calculations based on LLFS, 1994-2009.

Table 4: Decomposition of age group difference in duration, by gender

	Exit from Unemployment to Employment		
	Full sample	**Males**	**Females**
$O(\bar{x}_o) = \bar{\Gamma}(\hat{\alpha}_o)exp(\bar{x}_o'\hat{\beta}_o)$	40.98	45.52	65.47
$Y(\bar{x}_y) = \bar{\Gamma}(\hat{\alpha}_y)exp(\bar{x}_y'\hat{\beta}_y)$	24.08	27.30	19.17
Difference to be decomposed	16.9	18.22	46.3
$O(\bar{x}_o) = \bar{\Gamma}(\hat{\alpha}_y)exp(\bar{x}_o'\hat{\beta}_y)$	21.59	25.10	30.35
Structure effect	19.39	25.92	35.12
Composition effect	-2.49	-7.7	11.18
$O(\bar{x}_y) = \bar{\Gamma}(\hat{\alpha}_o)exp(\bar{x}_y'\hat{\beta}_o)$	24.57	51.92	86.48
Structure effect	16.41	-6.4	-21.01
Composition effect	0.49	24.62	67.31
Chow test	51.46	54.14	86.64
p value	7.286e-13	2.334e-25	1.422e-39

Notes: Length of unemployment are defined in months. The hazard function is given by the Weibull distribution.
Source: own calculations based on LLFS, 1994-2009.

Appendices

Appendix A Definitions and Data Construction

A.1 Variable definitions

Higher educational level: Advanced Level university entrance-level qualification or higher.

Private firms and non-profit organizations are classified as *private sector*.
Civil servants, employees in central and local government, town halls, the NHS, High Education, nationalized industries and in the armed forces are classified as *public sector*.

Part-Time Jobs: workers who work less than 30 hours per week.

Primary sector: if respondent works in agriculture, forestry and fishing; energy, water and supplies; extraction of minerals, manufacture of metals, mineral products and chemicals industry.
Commercial services: if respondent works in distribution; hotels and catering (repairs); transport and communication; banking, finance, insurance, business services, leasing and other services.
Non commercial services: if respondent works in metal goods, engineering and vehicles industries, other manufacturing industries and construction.

Small firm: less than less than 25 employees.
Medium firm: between 25 to 499 employees.
Large firm: more than 500 employees.

*U*nemployment Rate: Regional yearly unemployment rate.

A.2 About the data

To estimate the model with a binary regression, the data must be re-organized into individual-year format data. For each individual, there is one row each time interval at risk of the event occurs and each individual contributes as much he has row of risk of having an events. For example, if individual i is in employment 5 years and then leaves the labour force, this individual contributes 5 rows, the rows are the number of time periods that i was at risk of the event. The re-organization of the data allows an easy estimation of discrete-time hazards models and also to include time-varying variables.

Table A1: Sensitivity Analysis using a Logit Specification: Probability of re-employment by gender

	Males		Females	
	(1)	**(2)**	**(3)**	**(4)**
Age	-0.0737***		-0.0305	
	(0.0118)		(0.0195)	
Age_{55-59}		-0.302***		-0.455***
		(0.105)		(0.147)
Age_{60-64}		-0.786***		
		(0.135)		
A level or equivalent	0.232	0.204	0.366	0.344
	(0.161)	(0.135)	(0.230)	(0.230)
Higher education or college degree	0.145	0.139	0.459**	0.388*
	(0.122)	(0.122)	(0.220)	(0.223)
GCSE-O level and below	0.277*	0.280*	0.507**	0.487**
	(0.168)	(0.168)	(0.202)	(0.203)
Unemployment insurance benefit	0.150	0.144	-0.176	-0.120
	(0.099)	(0.101)	(0.149)	(0.149)
Sickness or disability benefit	-0.969***	-0.972***	-0.405	-0.379
	(0.293)	(0.293)	(0.400)	(0.400)
Observations (indiv.-spell)	22,054	22,054	7,922	7,922
Number of individuals	1,383	1,383	707	707
LR χ^2	828.5	825.7	388.2	392.4
Prob< χ^2	0.000	0.000	0.000	0.000
log likelihood	-1960.3	-1962	-911.3	-907.6

Notes: In addition to variables shown, an intercept and controls for education, household composition characteristics, race, health status, previous occupational status, firm characteristics, individuals' region of residence, regional unemployment rates, and dummy for yearly baseline hazard were included in all specifications. The baseline hazard rate is nonparametric.
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: own calculations based on LLFS, 1994-2009.

Table A2: Sensitivity Analysis using a Multinomial Logit Specification: Probability of re-employment by gender

	Males		**Females**	
	Employment	**Inactivity**	**Employment**	**Inactivity**
Age_{55-59}	-0.300**	0.033	-0.455**	0.025
	(0.104)	(0.136)	(0.147)	(0.146)
Age_{60-64}	-0.772***	0.542***		
	(0.135)	(0.137)		
A level or equivalent	0.208	0.186	0.338	-0.150
	(0.161)	(0.178)	(0.230)	(0.260)
Higher education or college degree	0.141	0.095	0.390*	0.055
	(0.122)	(0.138)	(0.222)	(0.223)
GCSE-O level and below	0.285*	0.246	0.497**	0.182
	(0.168)	(0.199)	(0.202)	(0.198)
Unemployment insurance benefit	0.140	-0.216*	-0.138	-0.554**
	(0.100)	(0.121)	(0.149)	(0.165)
Sickness or disability benefit	-0.943***	0.974***	-0.353	0.356
	(0.292)	(0.163)	(0.400)	(0.309)
Observations (indiv.-spell)	22,054	22,054	7,922	7,922
Number of individuals	1,383	1,383	707	707
LR χ^2	1327	1327	769	769
Prob< χ^2	0.000	0.000	0.000	0.000
log likelihood	-3739	-3739	-1808	-1808

Notes: In addition to variables shown, an intercept and controls for education, household composition characteristics, race, health status, previous occupational status, firm characteristics, individuals' region of residence, regional unemployment rates, and dummy for yearly baseline hazard were included in all specifications. The baseline hazard rate is nonparametric.
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: own calculations based on LLFS, 1994-2009.

Table A3: Specification Tests with a complementary log-log specification for the full sample

LR test	χ^2 (**Prob** $> \chi^2$)
1. Combining outcomes	
Pooled Exit and Employment	4005.5 (0.000)
Pooled Exit and Inactivity	5289.5 (0.000)
Employment and Inactivity	1283.96(0.000)
2. Parametric vs Nonparametric	1042.86 (0.000)

Table A4: Specification Tests with a multinomial specification for the full sample

	χ^2	**(Prob $> \chi^2$)**
1. Wald Test		
Combine Employment and Inactivity	236.89	(0.000)
Combine Employment and Unemployment	828.28	(0.000)
Combine Inactivity and Unemployment	218.04	(0.000)
2. LR Test		
Combine Employment and Inactivity	505.28	(0.000)
Combine Employment and Unemployment	1042.25	(0.000)
Combine Inactivity and Unemployment	289.67	(0.000)
3. Small-Hsiao test of IIA Assumption		
Omitted Employment	-1134.07	0.00 (against Ho)
Omitted Inactivity	-973.48	0.188 (for Ho)
4. Hausman test of IIA Assumption		
Omitted Employment	0.000	1.00 (for Ho)
Omitted Inactivity	5.981	1.00 (for Ho)

Figure 1: Employment rates in UK, by age

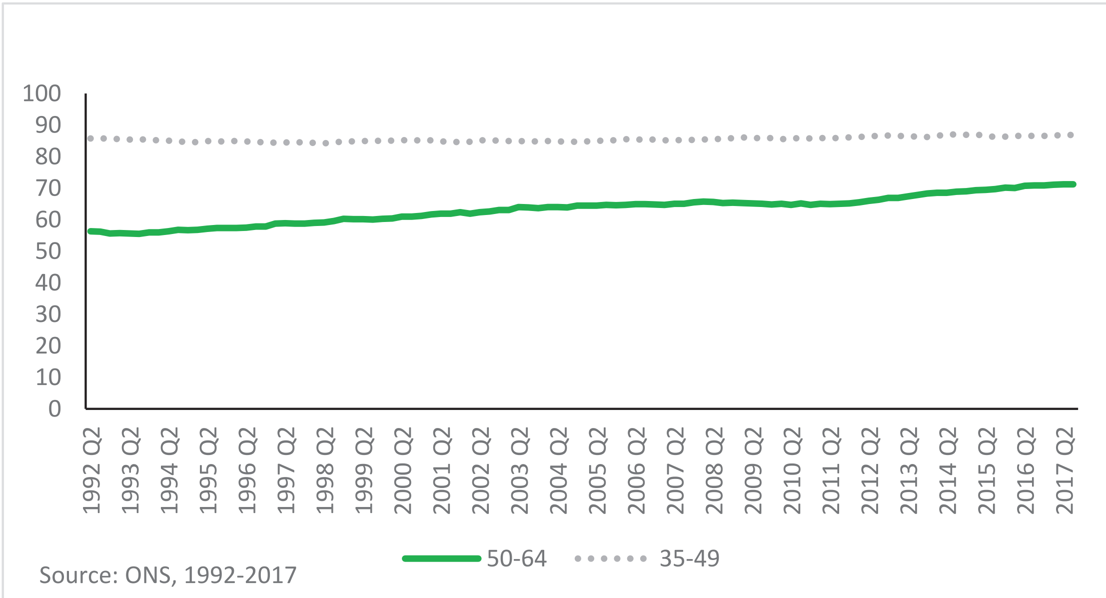

Figure 2: Unemployment rates in UK and proportion that are in long-term unemployment, by age