Influences of Recent History on the Early Career Patterns of Young Long-Term Unemployed Workers in Belgium*

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Abstract

By using a Belgian administrative dataset on young long-term unemployed workers and by applying duration techniques, the strategies for labour market reintegration, employability, and career stability of the disadvantaged youth are evaluated. The main results show that: i) the length of the previous job only mildly and not significantly decreases the reemployment probability; ii) rather, a job experience generates, *per se*, a positive effect on the unemployment exit rate; iii) conditional on job leaving, shorter-term jobs induce transitions into shorter-term and dead end positions; iv) no scarring effects on the stability of the subsequent job coming via the unemployment spell duration are found.

Keywords: duration analysis, transition intensity, unemployment, employment, lagged duration dependence.

JEL classification codes: C41, J62, J64

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1 Introduction

In recent years attention has been paid to the persistent and particularly high Belgian unemployment for certain groups, such as older and younger workers. With regard to the youth, the OECD (2007) has underlined that Belgium is performing worse than the OECD average in terms of labour market indicators. The European Union Labour Force Survey reported an average Belgian unemployment rate of 8.4% in 2005. Focusing on young workers, age 15–24, the unemployment rate was 21.5% and exactly equal to the rate in 1995. If we look instead at what has happened in the EU-15 area, we observe that for youths the unemployment rate has decreased from 21.2% in 1995 to 16.8% in 2005.

The concern that early labour market experiences may affect the subsequent career pattern and the high level of the Belgian youth unemployment rate in part justify the existence of unemployment benefits also for youth without any labour market experience. However, unemployment benefits might be an incentive to postpone the first labour market experience generating deterioration of human capital (Phelps 1972), stigma effects (Lockwood 1991, Pissarides 1992) and, consequently, negatively affecting future job opportunities (Piore 1971, Pissarides 1992, Pissarides 1994) and the incidence of aggregate long-term unemployment (Ljungqvist and Sargent 1998).

This paper focuses the relationship between recent labour market histories and the future career opportunities of the young Belgian unemployed who have no labour market experience, are 18–25 years old, and waited at least 9 months in "registered" unemployment to be entitled and receive unemployment insurance benefits. Our evaluation concerns this subset of the unemployed since the Belgian government sponsored further research to deepen the knowledge about the career profile of young disadvantaged workers.

In the last three decades several empirical investigations have studied the effect of current labour market outcomes on different aspects of future labour market performances. A branch of this literature has dealt with the impact of current unemployment spells on the propensity to experience unemployment in the future. Heckman and Borjas (1980) is a seminal paper on the effects of current duration, lagged duration, and lagged occurrence of an unemployment event on the probability of leaving unemployment in the US. Further evidence for the US was provided by, among others, Flinn and Heckman (1982b), Lynch (1989), and Omori (1997). Whether unemployment tends to bring unemployment in Europe was studied by Narendranathan and Elias (1993) and Arulampalam et al. (2000) for the UK and Mühleisen and Zimmermann (1994) for Germany. Much of the evidence indicates that unemployment tends to bring future unemployment. Gregg (2001) analysed instead whether in the UK youth unemployment has a long-term scarring effect in terms of later adult unemployment recurrence, finding a strong persistence of unemployment later in life.

Another branch has looked at the strategies leading the unemployed to better quality jobs. A variety of aspects of the quality of the jobs has been dealt with. Firstly, Stewart (2007) examined the extent to which unemployment and low-wage jobs have an adverse effect on future employment prospects in the UK. Low-wage employment was found not to be a springboard for stable jobs and to act as the main conduit for repeat unemployment. Uhlendorff (2006) found a strong link between low pay and unemployment in Germany.

A second aspect that has been evaluated is the impact of labour market events on subsequent earnings. This issue have been extensively analysed in the US and much of the evidence indicates a permanent scarring effect of unemployment on wages and that repeated job losses is an important factor behind this persistence (Jacobson et al. 1993, Stevens 1997, Spivey 2005). With regard to the UK, Arulampalam (2001) found that unemployment is scarring in terms of wages and that what particularly matters is the first unemployment experience; moreover, the Gregory and Jukes's (2001) study indicated that both unemployment occurrence and its duration have a negative effect on subsequent wages and the Gregg and Tominey's (2005) analysis found that a youth unemployment spell imposes a sizeable wage scar over the next twenty years.

A third aspect deals with the type of contract. In recent years, temporary employment has risen in almost all European countries and researchers have tried to understand whether temporary jobs are a stepping stone to permanent positions. Booth et al. (2002) and Zijl et al. (2004) found that temporary jobs are a stepping stone to permanent work in Britain and in the Netherlands, respectively. Gagliarducci (2005) pointed out that in Italy the probability of moving into regular employment decreases with job interruptions and repeated temporary jobs but temporary contracts seem to be a springboard to permanent positions (Picchio 2007). García Pérez and Muñoz-Bullón (2007) showed that in Spain temporary jobs do not constitute stepping stones towards permanent employment and that repeated temporary jobs decrease the probability of finding a stable job.

Finally, a scarce branch of this literature has assessed the effect of unemployment duration on the duration of the subsequent job. Böheim and Taylor (2002) studied the British job tenure by using a proportional hazard model. Previous labour market state and its duration are included in the specification of the job hazard rate. The main results show that unemployment incidence penalizes the duration of the subsequent job spell, whilst the duration of the previous unemployment spell only mildly affect the subsequent job tenure. Belzil (2001) and Tatsiramos (2004) focused on the effect of unemployment insurance respectively in Canada and in France, Germany, and the UK. They jointly modelled unemployment and employment hazard rate and negative correlation between unemployment duration and subsequent employment stability emerged.

Summarizing, the main findings indicate that the experience of unemployment and mildly its duration damage both the stability of subsequent employment and future wages. Accepting low-wage jobs to escape unemployment may result in a dead end position, whilst in some countries short-term contracts are not mere short-run reliefs from unemployment but may be a successful strategy to stable job relationships.

This paper is a contribution to this literature and tries to understand what strategies might lead the disadvantaged Belgian youth to better quality job relationships in terms of job stability. A duration analysis is performed through a multi-state multi-spell mixed proportional hazard model in a competing-risk framework. We allow for two possible states, unemployment and job. The durations of the previous labour market spell are included in the specification of the transition intensities as explanatory variables.

In contrast to the previous literature, unemployment to job, job to job, and job to unemployment transition intensities are jointly modelled, unobserved heterogeneity is taken into account, and both duration dependence and individual heterogeneity are specified in a flexible way. In this way, we first of all design a more general model than those of Belzil (2001), Böheim and Taylor (2002), and Tatsiramos (2004). Secondly, the flexible specification of both the duration dependence and unobserved heterogeneity contrasts with some parametric assumptions in Böheim and Taylor (2002) and Belzil (2001). Lastly, our estimation procedure controls for sample selection into multiple spells: even if multi-spell information improves identification of the unobserved heterogeneity distribution (Heckman and Singer 1984), workers who experience multiple spells may not be a random sample (Jurajda 2002). In contrast with Böheim and Taylor (2002), we control for this problem by jointly estimating unemployment and single job durations and by taking into account the presence of spell-correlated individual heterogeneity.

In summary, this study addresses these issues: i) Do shorter-lived job relationships matter in determining the reemployment probability in case of dismissal? ii) Is post-dismissal reemployment probability higher than post-schooling (no job experience) employment probability? iii) Do short-term job relationships arise from short-term jobs? iv) Does unemployment duration have a scarring effect on the stability of the subsequent job? Answering these questions will deepen the understanding of the mechanisms driving the labour market dynamics of the disadvantaged Belgian youth and might have an important implication in designing successful intervention and programmes that seek to improve labour market reintegration, employability, and career stability.

Since the unemployment state is identified through the entitlement to unemployment benefits, in section 2 we briefly clarify the main regulations about eligibility for and amounts of unemployment benefits. Section 3 illustrates the econometric model. Data and sample are described in section 4. The estimation results are reported and commented in section 5. Section 6 concludes.

2 The Belgian Unemployment Insurance System

In Belgium youth can acquire a time unlimited entitlement[1] to unemployment benefits in two ways: i) school-leavers below 30 years of age after a waiting period of 9 months;[2] ii) laid off unemployed workers are entitled if they regularly worked for a sufficient number of days.[3] The latter is common to many countries, whilst the former is less common, but also present with different and stricter eligibility schemes, in Denmark, Greece, Luxembourg, and Czech Republic (OECD 2004).

The amount of unemployment benefits for a laid off worker depends on the last wage, age, and household composition. For instance, in January 2007, the cohabitants in charge of the household received an unemployment insurance equal to the 60% of their last wage with a floor and a ceiling equal to 913€ and 1,078€, respectively. If they were not in charge of the household, they received 55% of the last wage within the range 575–988€ in the first year of unemployment, 40% within the range 575–719€ in the first three months of the second year of unemployment (additional three months per year of employment), and thereafter a time unlimited amount of 397€. The single workers received 60% of the last wage in the first year of unemployment

[1] See Cockx and Ries (2004) for the only exception of the indefinite period entitlement to unemployment benefits in Belgium.

[2] Actually, the duration of the waiting period is 6 months for youth below 18 years of age, 9 months for the 18–25 years old, and 12 months for the older than 26.

[3] Workers younger than 36 years of age become entitled to post-dismissal unemployment benefits if they satisfy one of the following requirement: i) they have worked at least 312 days during the last 18 months; ii) they have collected at least 468 working days during the last 27 months; iii) they have worked at least 624 days during the last 36 months. A quarter of full-time employment is counted on average as 78 working days; for part-timers it depends on the amount of worked hours.

and 50% thereafter, with floor-ceilings equal to the ranges 767–1,078€ and 767–898€, respectively.

After the waiting period the unemployed school-leavers are entitled to flat-rate time unlimited unemployment benefits. The amount depends on age and family conditions and since January 2007 it goes from a maximum of 889€ for the cohabitants in charge of the household to a minimum of 217€ for the cohabitants not in charge of the household and below 18 years of age.

3 The Econometric Model

This section deals with econometric modelling and elucidates the main steps taken to construct the likelihood function. Firstly, in subsection 3.1 notation, specification of the labour market transition intensities, and identification issues are clarified. Secondly, subsection 3.2 contains a discussion on the possible sources of endogeneity and the strategy adopted to take into account and to control for them. Finally, in subsection 3.3 the likelihood function to be maximized is derived.

3.1 Transition Intensities and Identification Issues

A multi-state multi-spell duration model is the core of the empirical analysis presented in this paper. There are 2 mutually exclusive labour market states which can be occupied at each moment of time: unemployment (u) and job (e). Data provide a firm indicator and job to job transitions are therefore identifiable. Three possible transitions are therefore observed: u-e, e-e, e-u.

Spells that are incomplete due to exit out of the labour force, participation to some labour market programmes, going back to school, and lost of unemployment benefits eligibility (because of cheating on some of the eligibility requirements) are treated as spells that are subject to independent right-censoring. Let us call such a destination state "inactivity". As pointed out by van den Berg and Lindeboom (1998), if there are unobserved characteristics affecting labour market transitions and the transitions to inactivity, the transition intensities estimates are inconsistent. Therefore, we have also performed the econometric analysis by explicitly modelling the transitions from unemployment and job spells to inactivity as an absorbing state and by allowing for stochastically related unobserved heterogeneity. Estimation results very similar to the ones we are going to present and comment in section 5 were obtained but not reported for sake of brevity.

Data provide quarterly grouped information. If we assume that data are generated by a discrete time process as in Abbring et al. (2002), consistency depends on the correct assumption about the timing of grouping of the stochastic duration process. It is indeed well known (Flinn and Heckman 1982a) that parameters are not invariant to the time unit. We therefore prefer to adopt a continuous time model in analysing the discrete time data (see e.g. Cockx 1997, van den Berg and van der Klaauw 2001, Cockx and Dejemeppe 2005, Dejemeppe 2005). Moreover, the transition intensities are assumed to be of the Mixed Proportional Hazard (MPH) form in a competing risks framework.

The transition intensity from the origin state j to the destination state k is denoted by θ_{jk}, with the ordered pair $(j,k) \in \mathscr{X} = \{(u,e),(e,e),(e,u)\}$. During the sth spell and after t_s quarters in state j, with $t_s \in \mathbb{N}_0$, it is specified in the following form:

$$\theta_{jk}(t_s|\mathbf{x}_{jk}(\tau_s+t_s),v_{jk}) = h_{jk}(t_s)\exp\{\boldsymbol{\beta}'_{jk}\mathbf{x}_{jk}(\tau_s+t_s)\}v_{jk} \quad \text{for } (j,k) \in \mathscr{X}, \tag{1}$$

where $h_{jk}(\cdot)$ is the baseline hazard which captures time dependence; v_{jk} is the transition-specific individual heterogeneity, a positive random number; $\mathbf{x}_{jk}(\tau_s+t_s)$ is a K_{jk} dimensional vector of time-invariant and time-variant covariates controlling for observed heterogeneity at the transition quarter (τ_s+t_s) and including the length of the preceding labour market spell, i.e. lagged duration of the previous labour market spell. The associated and conformable parameter vector to be estimated is $\boldsymbol{\beta}_{jk}$.

The set $\mathscr{X}$ of possible origin-destination states elucidates that there is a single exit from unemployment whilst multiple exits from job events. Abbring and van den Berg (2003) showed the identifiability of the MPH competing risks model under flexible assumptions on the specification of the baseline hazards and the unobserved heterogeneity.[4] Abbring (2006), using a repeated application of Abbring and van den Berg (2003), proved that under mild assumption the MPH competing risks model with lagged occurrence dependence is identified. However, the focus of this paper is on lagged duration dependence and the assumptions under which lagged duration dependence is identified in a MPH competing risks model are still unknown and represent ground for further research.[5] Nevertheless, if we focus on the unemployment state which has a single destination, Honoré (1993) can be invoked for the identification of lagged job duration on the specification of the u-e transition intensity.

[4]See also Heckman and Honoré (1989) for the presentation and the identifiability of single spell MPH competing risks models with unobserved heterogeneity.

[5]The nomenclature of lagged duration dependence and lagged occurrence dependence is the same as in Heckman and Borjas (1980).

3.2 Specification Issues

In this subsection the main sources of specification error that could affect our hazard model of event durations are, firstly, pointed out. Then, we describe how the components of the transition intensities in (1) are specified in order to face these econometric issues and avoid biased results.

The multi-state multi-spell duration model described by the transition intensities in (1) is chiefly aimed at estimating the impact of the previous labour market outcome on the subsequent job match quality (job duration) and subsequent unemployment duration. In doing that, endogeneity problems may arise because of ignoring unobserved heterogeneity that stochastically relates unemployment and job durations. There could be, for instance, some workers' characteristics not observed by the econometrician that are more appealing to employers and that therefore induce longer lasting unemployment spells and subsequent shorter-term jobs; if unobserved heterogeneity is not taken into account, lagged duration dependence could be spurious.

Moreover, it is well established that ignoring unobserved heterogeneity would bias downwards the estimates of the time dependence effects (Heckman and Borjas 1980) and generate spurious duration dependence. Spurious duration dependence could also arise by neglecting time-varying heterogeneity. For example, we have seen in section 2 that laid off workers who are single or cohabitants not in charge of the household face declines in the amount of unemployment benefits. This is likely to change the opportunity cost of search and leisure of the unemployed and, if neglected, to generate spurious unemployment duration dependence.

Another source of bias might be due to misspecification of functional forms. Indeed even if the v_{jk}'s, with $(j,k) \in \mathscr{X}$, take into account of the spurious effect of unobserved heterogeneity, inference can be sensitive to the assumptions on their distribution (Baker and Melino 2000). A similar limit is faced in choosing the functional form of the baseline hazard $h_{jk}(\cdot)$ and, as pointed out by van den Berg (2001), minor changes in the assumed parametric specification may produce very different parameter estimates and influence the estimation of other coefficients.

Let us now move on to the specification of the components of the transition intensities. In order to disentangle spurious from true duration dependence and to avoid parametric assumptions on the distribution of the unobserved heterogeneity, we assume, following Heckman and Singer (1984), that the triplet $v \equiv [v_{ue}, v_{ee}, v_{eu}]$ is a random draw from a discrete distribution function with a finite and (a priori) unknown number M of support points. The probabilities associated to the mass points sum to one and,

$\forall\ m = 1, \ldots, M$, are denoted by

$$p_m = \Pr(v_{ue} = v_{ue}^m, v_{ee} = v_{ee}^m, v_{eu} = v_{eu}^m)$$

and specified as logistic transforms:

$$p_m = \frac{\exp \lambda_m}{\sum_{g=1}^{M} \exp \lambda_g} \quad \text{with} \quad m = 1, \ldots, M \quad \text{and} \quad \lambda_M = 0.$$

A prespecified low number of support points may result in substantial bias. Therefore, as suggested by the Gaure et al.'s (2007) Monte Carlo simulations, the number M of support points is chosen to minimize the Akaike Information Criterion (AIC). Note that the specification of the unobserved heterogeneity does not impose perfect correlation or no correlation as in factor loading models. In this way, the relation imposed by factor loading models on the marginal distribution and the dependence of durations is avoided (van den Berg and Lindeboom 1998, van den Berg 2001).

The baseline hazard $h_{jk}(\cdot)$ is piecewise constant. In this way we have a flexible specification (the duration dependence pattern is allowed to be nonmonotonic) and mild parametric assumptions. The discrete time axis of each labour market spell is divided into q intervals $I_l = [\tau_l, \tau_{l+1}[$ with $l = 1, 2, \ldots, q$, $\tau_1 < \tau_2 < \ldots < \tau_q$, $\tau_q \in \mathbb{N}$, and $\tau_{q+1} = \infty$. The positive baseline intensity function can be written as

$$h_{jk}(t_s) = \exp\Big\{ \sum_{l=1}^{q} \alpha_{jkl} d_{jkl} \Big\}, \tag{2}$$

where d_{jkl} is a dummy indicator equal to 1 if a transition from state j to k occurs during interval I_l, and α_{jkl} is the corresponding intensity parameter to be estimated.[6] The form of the baseline hazard does depend on the rank order of the spell s in the sequence of labour market states. An exception is the baseline hazard of the u-e transition intensity: the u-e baseline hazard when $s = 1$ is allowed to have a different form from that of subsequent spells. Firstly, this is to take into account that when individuals enter the first unemployment spell they already have an elapsed unemployment duration of 9 months by sample design. Furthermore, in this way the functional form of unemployment duration dependence of individuals without job experience is allowed to be different from that of laid off workers. This further flexibility given to the function form of unemployment duration dependence

[6] The α_{jk1}'s are normalized to 0; these normalizations are innocuous because the scale of the θ_{jk}'s is captured by the v_{jk}'s.

might capture: i) a lagged occurrence dependence effect, i.e. the impact on the level of the baseline hazard due to previous job experiences rather than being school-leaver;[7] ii) an heterogeneous impact of the deterioration of human capital (general skills) on the unemployment duration pattern for worker with and without job experiences.

Even if we control for individual heterogeneity and we model the baseline hazards in a flexible way, we are aware that parameter estimates attached to the other covariates could be bias by some other source of unobserved heterogeneity. As pointed out by Horny et al. (2006), since decision on job mobility involves both the worker and the firm, job transition rates could be simultaneously affected both by workers' and firms' heterogeneity. In this paper we do not extensively deal with unobserved firm heterogeneity and this is left for further research.

Finally, the set of covariates $\mathbf{x}_{jk}(\tau_s + t_s)$ controlling for observed heterogeneity can be decomposed into three sub-vectors:

- $\mathbf{x}^0_{jk}$ is the set of time-invariant covariates that are fixed at the date of entrance into the sample. This vector includes dummies for nationality, region of residence, and education.
- $\mathbf{x}^1_{jk}(\tau_s)$ is the set of time-variant variables that are fixed at the date of entrance into the sth spell and then remain constant through the spell. This vector includes age, local unemployment rate, quarter of entry into the spell, and the length of the last labour market spell. If the origin state is e, then a set of dummies controlling for firm heterogeneity (sector and firm size) is also added. As the amount of the unemployment benefits depend on the household position,[8] we control for it by including household position dummies. Even if information on the benefit levels is provided, there are several missing values at the entry date in the sample. Since, conditional on household position, summary statistics by quarter on the observed amount of unemployment benefits revealed standard deviations often close to zero, we believe that the household position dummies successfully control for the benefit levels.
- $\mathbf{x}^2_{jk}(\tau_s + t_s)$ is the sub-vector of covariates varying within the sth spell. The u-e transition intensity is exclusively characterized by such variables. In order to remove spurious unemployment duration dependence possibly generated by declines in the amount of unemployment benefits over unemployment duration, we follow Meyer (1990). By denoting τ the number of quarters until benefits decline and noting that nobody in

[7] By school-leavers we refer to those who have completed their schooling, are not going directly to further education, and have not found their first job (for at least 3 quarters).

[8] See section 2.

the sample is more than 4 quarters away from a decline in the amount of unemployment benefits the following variables are included: $UI\ 1 = 1$ if $\tau = 1$, and 0 otherwise; $UI\ 2 = 1$ if $\tau \leq 2$, and 0 otherwise; $UI\ 3 = 1$ if $\tau \leq 3$, and 0 otherwise; $UI\ 4 = 1$ if $\tau \leq 4$, and 0 otherwise. For example, the coefficient of $UI\ 1$ captures the marginal effect of going from 2 quarters to 1 quarter away from the benefits decline; the coefficient of $UI\ 2$ is the marginal effect of going from 3 quarters to 2 quarter away from the benefits decline. Similar interpretation applies to the coefficients of $U3\ 1$ and $UI\ 4$.

3.3 Constructing the Likelihood Function

3.3.1 Survivor Functions

The competing risks duration model with MPH hazard intensities is estimated by Maximum Likelihood. We are now going to write down the contribution to the likelihood function of the generic spell s of a representative individual. For doing that, it is useful to specify survivor functions by state of origin.

Denote $\mathscr{U} = \{(u, e)\}$ and $\mathscr{E} = \{(e, e), (e, u)\}$ the sets of ordered pairs of origin and destination states that are accessible from unemployment and job, respectively. The probability of surviving into unemployment in spell s for t_s quarters can be written as

$$S_j(t_s|\mathbf{x}_j(\tau_s + t_s), v_j) = \prod_{\tau=1}^{t_s} \exp\Big\{-\sum_{(j,k)\in\mathscr{J}} \theta_{jk}(\tau|\mathbf{x}_{jk}(\tau_s + \tau), v_{jk})\Big\}, \tag{3}$$

where $\mathscr{J} = \mathscr{E}$ if $j = e$ and $\mathscr{J} = \mathscr{U}$ if $j = u$, $\tau \in \mathbb{N}$, and $\mathbf{x}_j(\tau_s + t_s)$ and v_j collect, respectively, the $\mathbf{x}_{jk}(\tau_s + t_s)$'s and the v_{jk}'s with $(j, k) \in \mathscr{J}$.[9]

3.3.2 Single-Spell Contribution to the Likelihood Function

Let us consider spell s of individual i and suppose that individual i survives t_s quarters in the origin state j and then she makes a transition to state k. The contribution to the likelihood function of this single complete spell is given by the probability of observing a j-k transition between the t_sth quarter and the previous one, conditional on observables and unobservable

[9] Equation (3) is derived from a standard continuous time model where the transition intensities are assumed to be constant within each pair of consecutive quarters. See appendix A-1 for further details about the specification of the discrete time process as a continuous time model; alternatively, see Cockx (1997).

characteristics:[10]

$$L_{is}(\Theta_j|t_s,\mathbf{x}_j(\tau_s+t_s),v_j) = \frac{\theta_{jk}(t_s|\mathbf{x}_{jk}(\tau_s+t_s),v_{jk})}{\sum_{(b,c)\in\mathscr{J}}\theta_{bc}(t_s|\mathbf{x}_{bc}(\tau_s+t_s),v_{bc})} \times \left[S_j(t_s-1|\mathbf{x}_j(\tau_s+t_s-1),v_j) - S_j(t_s|\mathbf{x}_j(\tau_s+t_s),v_j)\right] \quad (4)$$

for $j \in \{u,e\}$,[11] where:

- Θ_j is the set of parameters entering the contribution to the likelihood function of a complete spell of which the origin state is j.
- The difference in square brackets is the probability of leaving state j between the $t_s - 1$th quarter and the t_sth quarter.
- The ratio is the instantaneous probability of making a j-k transition, conditional on leaving j after a sojourn of t_s quarters.

The contribution to the likelihood of an incomplete spell (right-censored) of length t_s is simply the probability of surviving in the origin state j until the end of the observation period without making any transition:

$$L_{is}(\Theta_j|t_s,\mathbf{x}_j(\tau_s+t_s),v_j) = S_j(t_s|\mathbf{x}_j(\tau_s+t_s),v_j) \quad \text{for } j \in \{e,u\}. \quad (5)$$

3.3.3 Individual Contribution to the Likelihood Function

Let us call S_i the number of labour market spells experienced by individual i, so that $s = 1,\ldots,S_i$. Then, the individual i's contribution to the likelihood function is given by the product over the spells, from 1 to S_i, of the single-spell contributions to the likelihood function. In order to remove from the likelihood function the unobservable individual heterogeneity, we integrate it out exploiting the discrete distributional assumption. Therefore, the individual i's contribution to the likelihood function can be written as:

$$L_i(\Theta|t_{i1},\ldots,t_{iS_i},\mathbf{x}_i(\tau_1+t_1),\ldots,\mathbf{x}_i(\tau_{S_i}+t_{S_i}),M) = \sum_{m=1}^{M} p_m\Big[\prod_{s=1}^{S_i} L_{is}(\Theta_e,v_e^m|t_{is},\mathbf{x}_{ie}(\tau_s+t_s))^{d_{is}} L_{is}(\Theta_u,v_u^m|t_{is},\mathbf{x}_{iu}(\tau_s+t_s))^{(1-d_{is})}\Big], \quad (6)$$

where:

[10] We drop the subscript i to simplify the notation.

[11] Equation (4) is the unconditional probability of leaving j for k within quarter $t_s - 1$ and t_s and, similarly to equation (3), is derived from a continuous time model where the transition intensities are assumed to be constant within each pair of consecutive quarters. See appendix A-1 for details.

- $\Theta = \Theta_e \cup \Theta_u \cup \{(p_1, v_e^1, v_u^1), \ldots, (p_M, v_e^M, v_u^M)\}$ is the set containing all the parameters to be estimated.
- $\mathbf{x}_i(\tau_s + t_s) = [\mathbf{x}_{ie}(\tau_s + t_s), \mathbf{x}_{iu}(\tau_s + t_s)] \; \forall \; s = 1, \ldots, S_i$.
- d_{is} is a dummy indicator equal to 1 if the sth spell of individual i is a job spell and equal to 0 if it is an unemployment spell.

3.3.4 The Log-Likelihood Function

Once we have defined the individual contributions to the likelihood function, we can derive the global log-likelihood function summing the log of the individual contributions. The log-likelihood function we maximize with respect to the set of parameters Θ is therefore the following:

$$\ell(\Theta|\mathbf{t}_1, \ldots, \mathbf{t}_S, \mathbf{X}(\tau_1 + t_1), \ldots, \mathbf{X}(\tau_S + t_S), M) = \sum_{i=1}^{N} \ln L_i(\Theta|t_{i1}, \ldots, t_{iS_i}, \mathbf{x}_i(\tau_1 + t_1), \ldots, \mathbf{x}_i(\tau_{S_i} + t_{S_i}), M), \tag{7}$$

where $\mathbf{t}_s$ and $\mathbf{X}(\tau_s + t_s)$ indicate the N-rows dimensional matrices collecting respectively spell s durations and spell s covariates for all the individuals and S is the maximum number of spells in our sample. Function (7) is maximized with respect to Θ using a subspace trust region approach based on the interior-reflective Newton method.

4 Data

For the empirical analysis we used administrative data provided by the Belgian *Banque Carrefour de la Sécurité Sociale*, which collects and organizes data from several social insurance institutions. Our sample is made up of 14,961 young unemployed school-leavers without any labour market experience, 18–25 years old in 1998 and that, during this year, were entitled for the first time to unemployment benefits. The econometric analysis is conducted after separating the sample by gender. The female sample includes 8,572 individual records. The male sample is made up of 6,389 individual observations.

The entrance in the sample occurs in 1998 on the basis of monthly information. Thereafter, information is provided on a quarterly basis until the end of 2001; the longitudinal dimension is then composed by 16 time observations. Since the entrance in the sample can take place within a quarter and when individuals enter they have already spent 3 quarters in unemployment, the probability of leaving the first unemployment spell during the 4th quarter of unemployment will be underestimated.

Figure 1 provides by gender an overview of the first labour market experiences of the Belgian young long-term unemployed and table 1 reports descriptive statistics about the number of spell-individual observations by gender. The maximum number of different spells is 12 and the average is around 2.5 per individual during the 4 years observation window. Men are more mobile than women; 40% of the male sample and 34% of the female sample experience at least 3 spells. This multi-spell information is exploited to infer the impact of the lagged labour market durations on the current transition intensities.

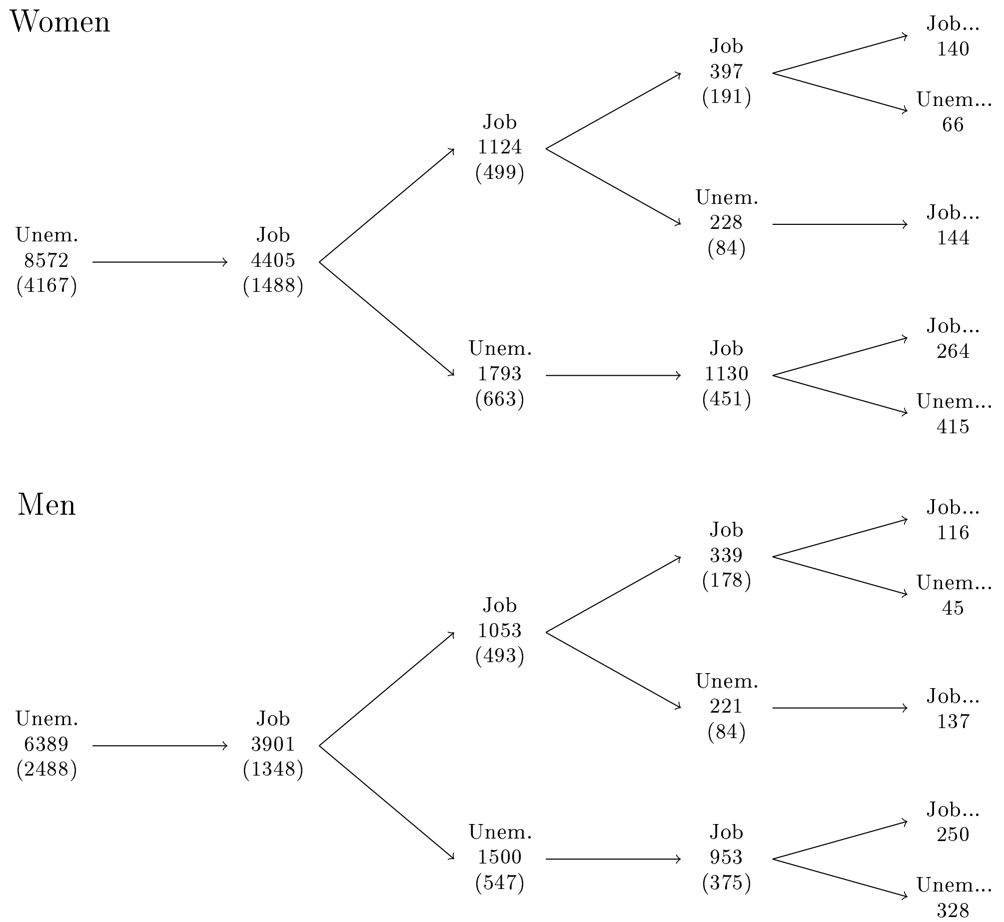
Data contain information about individual, family, and job characteristics that is used to control for individual and job heterogeneity. Table 2 displays summary statistics for the time-invariant explanatory variables and for the time-variant ones at sampling date. Most of the young long-term unemployed are Belgian (88.3%), with at least a higher secondary school diploma (61%), and living in Wallonia (65.7%). The female unemployed are more educated: 65.6% of the female sample has at least a higher secondary school disploma against 54.8% for men. The average age in 1998 is around 21.5 years and the average local unemployment rate is 18.5% for men and 26.9% for women.[12]

Table 1: Spell-Individual Observations by Gender

Number of spells (Unemployment + job spells)	Male		Female	
1	6,389	100.0%	8,572	100.0%
2	3,901	61.1%	4,405	51.4%
3	2,553	40.0%	2,917	34.0%
4	1,513	23.7%	1,755	20.5%
5	876	13.7%	1,029	12.0%
6	492	7.7%	577	6.7%
7	265	4.1%	326	3.8%
8	132	2.1%	181	2.1%
9	70	1.1%	95	1.1%
More than 9	49	0.8%	117	1.4%
Total observed spells	16,240		19,974	
Average spells per individual	2.542		2.330	

[12]The local unemployment rate is not computed following the ILO definition but is provided by the Belgian Unemployment Office (ONEM). It is the percentage of population insured against the risk of unemployment and since the denominator is smaller than the actual labour force, it is higher than the ILO unemployment rate.

Figure 1: Absolute Frequencies of the First Four Transitions by Gender



Note: In brackets are the numbers of right-censored spells.

Table 2: Summary Statistics by Gender

	Male		Female		Total	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Time-Invariant Variables						
Nationality						
Belgian	.890	.312	.877	.329	.883	.322
Non-Belgian EU	.051	.220	.055	.227	.053	.224
Non EU	.059	.235	.069	.253	.064	.245
Education						
Primary (6 to 9 years of schooling)	.122	.327	.080	.271	.098	.297
Lower secondary (9 to 12 years)	.279	.448	.224	.417	.247	.431
Higher secondary (12 to 14 years)	.424	.494	.484	.500	.458	.498
Higher education (16 years or more)	.124	.330	.172	.377	.152	.359
Other	.009	.096	.008	.089	.009	.092
Unknown	.042	.199	.032	.177	.036	.187
Region of residence						
Flanders	.195	.396	.242	.428	.222	.416
Wallonia	.678	.467	.642	.479	.657	.475
Brussels	.127	.334	.116	.320	.121	.326
Time-Variant Variables at Sampling Date						
Age	21.5	2.0	21.6	2.0	21.6	2.0
Local unemployment rate[(a)]	.185	.068	.269	.085	.233	.089
Quarter of entry						
January-February-March	.080	.271	.071	.257	.075	.263
April-May-June	.665	.472	.695	.460	.682	.466
July-August-September	.162	.369	.159	.366	.161	.367
October-November-December	.093	.290	.074	.262	.082	.274
Household Position						
Head of household	.076	.266	.110	.313	.096	.294
Single	.135	.342	.102	.303	.116	.321
Cohabitant	.788	.409	.788	.409	.788	.409
Observations	6,389		8,572		14,961	

[(a)] See footnote 12.

5 Estimation Results

Since our primary focus is on the effects of previous labour market duration on subsequent labour market performance, subsection 5.1 concentrates on the estimation results that answer the main research questions of this study. Duration dependence effects are dealt with in subsection 5.2. Other estimation results of interest are reported in subsection 5.3. Finally, subsection 5.4 focuses on the estimated parameters of the discrete distribution of the individual heterogeneity.[13]

5.1 Influences of Recent History on Subsequent Labour Market Spells

The first question we try to answer is whether the length of the previous job matters in determining the reemployment probability for laid off workers. Theoretical considerations have suggested two channels through which job tenure affects the subsequent reemployment speed. On one hand, laid off workers with longer job tenure face a higher loss of specific human capital and rise their reservation wages in order to restart the career from the level attained before their dismissals (Ljungqvist and Sargent 1998). This generates a negative correlation between job tenure and subsequent unemployment exit rate. On the other hand, displaced workers with a longer and stabler recent job experience may signal to a potential employer a higher capability to generate satisfactory job matches or a higher level of accumulated general human capital (Lockwood 1991). Looking at table 3, which reports by gender the estimation results on lagged and occurrence duration dependence, we note that lagged job tenure decreases the reemployment probability. The former theoretical prediction dominates the latter, but the sizes and the significance of the estimated coefficients are poor.

Nevertheless, figure 2, by depicting and contrasting the unemployment duration patterns of school-leavers and laid off workers, indicates that signalling exerts its effect not through the length of the last job but through the occurrence of a job experience. The probability of finding a job of laid off workers is always higher than that of individuals without any labour market experience, especially for women. This is a lagged job occurrence effect in the sense that the probability of leaving unemployment increases as soon as a job has been experienced. The unemployed endowed with some job experience may be more attractive to employers because of some accumulation

[13] In appendix A-3, tables A-2, A-3, and A-4 report estimation results of the duration model for men and women without individual heterogeneity.

of general human capital and may signal a higher level of productivity than that of unemployed school-leavers.

Table 3: Lagged Duration Dependence Estimation Results with and without Unobserved Heterogeneity

Transition	*u-e*		*e-e*			*e-u*		
Variable	Coeff.	S.E.	Coeff.	S.E.		Coeff.	S.E.	
			Men					
With unobserved heterogeneity								
Lagged job tenure	-0.010	0.02	-0.042	0.02	*	-0.143	0.04	***
Lagged unemployment	–	–	-0.009	0.01		0.004	0.01	
Previous state: unemployment	–	–	-0.010	0.10		0.212	0.12	*
Neglecting unobserved heterogeneity								
Lagged job tenure	-0.011	0.02	-0.069	0.02	***	-0.201	0.03	***
Lagged unemployment	–	–	-0.049	0.01	***	0.001	0.01	
Previous state: unemployment	–	–	-0.092	0.08		0.173	0.10	*
			Women					
With unobserved heterogeneity								
Lagged job tenure	-0.030	0.02	-0.036	0.02	*	-0.070	0.03	**
Lagged unemployment	–	–	-0.027	0.01	**	-0.001	0.01	
Previous state: unemployment	–	–	-0.082	0.09		0.401	0.11	***
Neglecting unobserved heterogeneity								
Lagged job tenure	-0.019	0.02	-0.060	0.02	***	-0.010	0.03	***
Lagged unemployment	–	–	-0.041	0.01	***	-0.007	0.01	
Previous state: unemployment	–	–	-0.203	0.07	***	0.445	0.09	***

Notes: * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Policy interventions aimed for speeding up the job-matching process for long-term unemployed school-leavers, for instance by an initial period of wage subsidy specific to these kind of individuals, will lower the aggregate average duration of unemployment also through the post-dismissal signalling channel.

Let us now move on to the impact of recent labour market history on job stability. First note that the job destruction rate depends on the origin state: job relationships starting from unemployment are more likely to be dead end positions. This effect is especially strong for women and barely significant for men.

Accumulation of general human capital, gains of productivity-skills (Dustman and Meghir 2005), and information externalities (Lockwood 1991) during the job tenure suggest that, conditional on job leaving, individuals with longer recent job tenures are more attractive to employers and more easily find stabler subsequent jobs. Here we find that, contrasting two workers both coming from another job, the one whose previous job was shorter-lived, is more likely to find a shorter-term or a dead end position. In other words, a recent history of job stability reduces the destruction rate of the ongoing job. The effect is especially strong and significant on the job destruction rate:

Figure 2: Estimated Baseline Hazards out of Unemployment with Unobserved Heterogeneity: First Unemployment Spell vs Subsequent Unemployment Spells.

Note: Relative unemployment duration dependence patterns are depicted. The reference is the reemployment probability after one quarter of post-dismissal unemployment which is set to 1.

one more quarter of tenure spent in the previous job decreases the transition intensity from the current job to unemployment by 14.3% for men and 7% for women. If we take a look at the corresponding estimation results from the models neglecting unobserved heterogeneity, we realize that they are biased downwards. By the direction of the bias we can infer that, conditional on observed covariates, those who experience longer job spells are also those who tend to experience lower subsequent job destruction rates.

The lagged job tenure has also a negative, but smaller, impact on the current job to job transition intensity. The point estimates suggest that one more quarter of duration of the previous job decreases the job to job transition intensity by nearly 4.2% for men and 3.6% for women. Nevertheless, these estimated coefficients are barely significant.

Then, interventions aimed for marginally extending the length of atypical temporary jobs (e.g. fixed-term contracts and contracts for temporary work agencies) can rise the young disadvantaged workers' probability of finding a more stable job at the end of the temporary relationship, reduce the repetition of short-term jobs, and, above all, lower the transition intensity into future dead end positions. Such programmes could be focal from the policy maker viewpoint considering the expansion of temporary contracts among younger workers in the last decade.[14]

[14] According to the European Union Labour Force Survey the fraction of Belgian temporary workers between 15 and 24 years of age went from 18.3% in 1995 to 32.1% in 2005. If we consider workers between 55 and 49 years of age, this rate was 4.3% in 1995 and 7.1% in 2005.

Finally, through the estimated coefficients of the lagged unemployment duration we can understand whether unemployment duration have a scarring effect on the stability of the subsequent job. The theoretical literature suggests that lagged unemployment duration are positively related to subsequent job separation rates when the longer-term unemployed are forced to look for a job in a secondary labour market (Piore 1971, Pissarides 1992, Pissarides 1994) characterized by shorter-term and dead end jobs. Nevertheless, it has also been suggested that the longer the search for a job, the higher the probability of a better match quality that is less likely to be dissolved (Burdett 1979, Marimon and Zilibotti 1999). The results obtained here indicate that the length of the last unemployment spell does not affect the male subsequent job tenure. The point estimates are negligible and not well determined. For women, the longer the last unemployment spell, the lower the subsequent job separation rate. The latter theoretical prediction seems to dominate the former. However, only the impact on the job to job transition intensities is significant and not negligible: one more quarter in unemployment reduces the probability of moving from the subsequent job to another one of about 2.7%.

Hence, the length of unemployment do not damage the stability of the subsequent job; rather, women gain in terms of lower propensity to experience job to job transitions.

5.2 Duration Dependence

In this subsection duration dependence patterns displayed by unemployment and job transition intensities are dealt with. Figure 2 depicts unemployment duration patterns and it has been partly introduced in the previous subsection.

The duration pattern of the first unemployment spell is nonmonotonic and roughly constant. Looking at the unemployment duration dependence of subsequent spells, both for men and women the steeper negative duration pattern occurs between the 3rd and the 7th quarter of unemployment. Then, the exit probability displays a constant profile and, after the 9th quarter of unemployment, it mildly increases for women and nearly reaches its initial level for men. The laid off workers' declining profile of the duration dependence pattern during the first 2 years of unemployment contrasts with the Cockx and Dejemeppe's (2005) results for young men in Wallonia (Belgium). They indeed found no unemployment duration dependence. However, their single-spell model did not distinguish, in estimating the baseline hazards, between first and post dismissal unemployment spells and did not control for the decline in the amount of unemployment benefits for some groups (see section 2).

Figure 3 depicts the duration patterns of e-e transition intensity (upper panel) and e-u transition intensity (lower panel). The two patterns display the same profile and they show nonmonotonically decreasing job separation rates. This finding is consistent with the central facts about working mobility (e.g. Topel and Ward 1992, Farber 1999): most new jobs end early and the job separation rate declines with tenure. More in details, the job separation rate declines until the 3rd quarter of tenure and then displays a peak during the 4th quarter. This peak might be due to the end of yearly temporary contracts that are not renewed. The job separation rate is fairly flat beyond the 5th quarter of job tenure.

Figure 3: Estimated Baseline Hazards out of Job with Unobserved Heterogeneity.

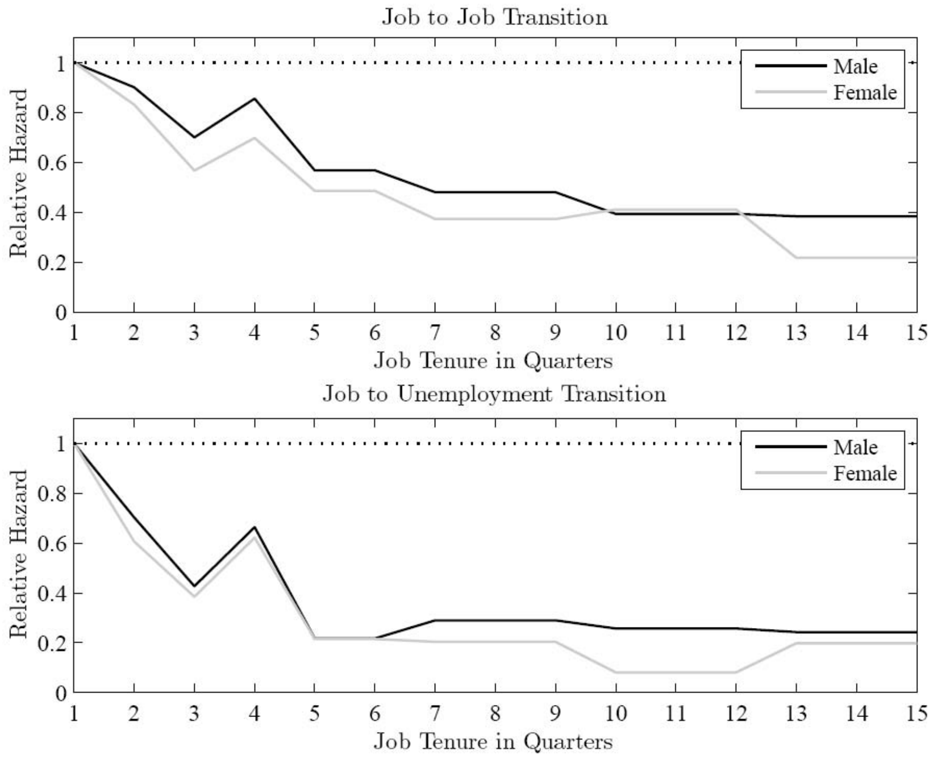


Table 4 reports the point estimates of coefficients and standard errors of the baseline hazards from the model with unobserved heterogeneity.[15]

[15] Table A-2 instead collects the estimated coefficients and standard errors of the baseline hazards from the model that neglects unobserved heterogeneity.

Table 4: Estimation Results of the Baseline Hazards

Transition	u-e, s=1				e-e			e-u		
Quarters	Coeff.	S.E.		Quarters	Coeff.	S.E.		Coeff.	S.E.	
				Men						
5th	0.615	0.05	***	2nd	-0.104	0.07		-0.352	0.06	***
6th	0.505	0.06	***	3rd	-0.356	0.08	***	-0.852	0.09	***
7th	0.350	0.07	***	4th	-0.156	0.09	*	-0.410	0.09	***
8th-9th	0.617	0.07	***	5th-6th	-0.565	0.10	***	-1.529	0.13	***
10th-12th	0.533	0.08	***	7th-9th	-0.734	0.11	***	-1.238	0.12	***
13th-15th	0.583	0.10	***	10th-12th	-0.935	0.17	***	-1.360	0.19	***
16th-19th	0.235	0.14	*	13th-15th	-0.958	0.38	***	-1.416	0.43	***
Rescaling factor[(a)]	-1.413	0.08	***							
	u-e, s>1									
2nd	-0.143	0.08	*							
3rd	-0.131	0.09								
4th	-0.318	0.13	**							
5th-6th	-0.495	0.13	***							
7th-9th	-0.654	0.19	***							
10th-13th	-0.047	0.29								
Transition	u-e, s=1				e-e			e-u		
Quarters	Coeff.	S.E.		Quarters	Coeff.	S.E.		Coeff.	S.E.	
				Women						
5th	0.551	0.05	***	2nd	-0.184	0.06	***	-0.499	0.06	***
6th	0.557	0.06	***	3rd	-0.568	0.08	***	-0.954	0.08	***
7th	0.422	0.07	***	4th	-0.359	0.08	***	-0.474	0.08	***
8th-9th	0.508	0.07	***	5th-6th	-0.721	0.09	***	-1.538	0.10	***
10th-12th	0.443	0.08	***	7th-9th	-0.987	0.10	***	-1.592	0.11	***
13th-15th	0.224	0.10	**	10th-12th	-0.888	0.14	***	-2.513	0.24	***
16th-19th	-0.090	0.13		13th-15th	-1.530	0.42	***	-1.621	0.38	***
Rescaling factor[(a)]	-1.609	0.08	***							
	u-e, s>1									
2nd	-0.138	0.07	*							
3rd	-0.022	0.09								
4th	-0.288	0.13	**							
5th-6th	-0.443	0.13	***							
7th-9th	-0.559	0.18	***							
10th-13th	-0.425	0.33								

Notes: * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
[(a)] By rescaling factor we refer to the intercept that characterizes the u-e transition intensity of the first unemployment spell. In the specification of the u-e transition intensity we have indeed allowed the unemployment baseline hazard of the first unemployment spell to take a different form from that of subsequent unemployment spells, whilst the impact of the systematic part and of the unobserved heterogeneity have been instead supposed to be independent on the rank order of the current spell. Therefore, if we had not introduced a different intercept, the baseline hazard of the first unemployment spell would have had the same reference as that of subsequent unemployment spells, without taking into account that when individuals enter the first unemployment spell they have already spent 3 quarters into unemployment.

5.3 Other Coefficients of Interest

In the literature it has been argued and found that *age* might have a positive effect on the length of unemployment (see, among others, the early studies by MacKay and Reid (1972) and Lancaster (1979)). For example, hiring standards could discriminate against older employees because of economic and institutional reasons and the job-search intensity may be affected by age. We instead find that, *ceteris paribus*, age has a negative impact on unemployment duration for men and a nil effect for women. This could be due to: firstly, our analysis is conducted on a sample of young individuals, hence relatively homogeneous in terms of age; secondly, age captures, among the individuals with at least a *higher education*, higher and time consuming educational degrees. Job tenure is expected to be positively related to the younger workers' age because of the learning process on their own preferences and on the mechanisms of the labour market (Stigler 1962). The only effect we find is that the male job to job hazard is positively affected by age. If, conditional on education, age captures longer lasting university degrees or postgraduate education, then this result could be explained by the Sicherman's (1990) prediction, according to which higher education might be correlated with a planned and more intense job mobility for an optimal career path.

Both women and men are less likely to escape unemployment when the local unemployment rate is high. Its impact on job tenure indicates that job relationships starting when the unemployment rate is higher are less stable and characterized by a larger destruction rate. The magnitude of this effect is similar for men and women, but it is significant only for women.

Non-EU women are less likely to find a job, whilst non-UE men are more likely to get a dead end position. The non-Belgian UE workers' probability of finding a job and job separation rates are not significantly different from those of comparable Belgian workers.

The (re)employment probability is higher for more educated workers who are also less likely to be fired. This evidence supports the idea that more educated workers are better endowed with human capital and skills so that they face a larger job market, search more efficiently, faster exit the unemployment pool (Mincer 1991), and produce higher quality job matches.

Flanders are characterized by a lower unemployment rate and, consistently, both Flemish men and women of our sample move faster to employment. Moreover, they are more likely to experience job to job transitions, and their job destruction rate is higher, but not significantly, than the one in Wallonia.

The household position plays an important role in explaining (re)employ-

Table 5: Estimation Results of the Systematic Parts – Men

Transition	*u-e*			*e-e*			*e-u*		
Variable	Coeff.	S.E.		Coeff.	S.E.		Coeff.	S.E.	
Age	0.023	0.01	**	0.030	0.02	**	-0.006	0.02	
Unemployment rate	-0.013	0.00	***	0.010	0.01		0.009	0.01	
Nationality - Reference: Belgian									
Non-Belgian EU	0.004	0.08		-0.023	0.13	*	0.108	0.10	
Non-EU	-0.124	0.08		0.061	0.13		0.220	0.11	**
Education - Reference: Higher secondary									
Primary school	-0.590	0.06	***	-0.025	0.11		0.603	0.10	***
Lower secondary	-0.390	0.05	***	-0.037	0.07		0.399	0.07	***
Higher education	0.353	0.06	***	0.149	0.08	*	-0.267	0.09	***
Other	-0.530	0.19	***	-0.283	0.39		0.302	0.25	
Unknown	0.831	0.12	***	-0.342	0.13	**	-2.555	0.32	***
Region of residence - Reference: Wallonia									
Flanders	0.203	0.07	***	0.447	0.10	***	0.144	0.10	
Brussels	0.035	0.06		-0.194	0.10	**	-0.059	0.08	
Household position - Reference: Cohabitant									
Head of household	-0.564	0.06	***	-0.056	0.10		0.323	0.09	***
Single	-0.251	0.05	***	0.101	0.07		0.384	0.07	***
Quarter of entry in the spell - Reference: April-May-June									
January-February-March	0.058	0.05		0.005	0.07		0.352	0.07	***
July-August-September	-0.099	0.05	**	0.049	0.07		0.252	0.07	***
October-November-December	-0.091	0.05	*	0.010	0.07		0.262	0.07	***
Firm size - Reference: 500 or more employees or Unknown									
$[1, 20)$ employees	–	–		-0.207	0.06	***	-0.344	0.06	***
$[20, 50)$ employees	–	–		-0.220	0.10	**	-0.279	0.10	***
$[50, 100)$ employees	–	–		-0.247	0.12	**	-0.201	0.12	*
$[100, 500)$ employees	–	–		-0.197	0.07	***	-0.219	0.07	***
Sector - Reference: Business services or Unknown									
Agriculture	–	–		-0.620	0.19	***	0.423	0.14	***
Industry & Mining	–	–		-1.195	0.09	***	-0.789	0.09	***
Building & Energy	–	–		-0.925	0.10	***	-0.971	0.10	***
Wholesale & Retail trade	–	–		-1.169	0.08	***	-0.923	0.07	***
Credit & Insurance	–	–		-1.107	0.20	***	-1.155	0.26	***
Other services & Pub. Adm.	–	–		-1.496	0.08	***	-0.899	0.07	***
Decline of unemployment benefits[(a)]									
UI 4	-0.229	0.13	*	–	–		–	–	
UI 3	0.174	0.19		–	–		–	–	
UI 2	-0.329	0.27		–	–		–	–	
UI 1	0.447	0.36		–	–		–	–	
# of observations									6,389
# of spells									16,240
# of parameters									122
Log-likelihood									-27,252.3
AIC/# of observations									8.569

Notes: * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
[(a)] The benefits decline variables are defined in subsection 3.2.

Table 6: Estimation Results of the Systematic Parts – Women

Transition	*u-e*			*e-e*			*e-u*		
Variable	Coeff.	S.E.		Coeff.	S.E.		Coeff.	S.E.	
Age	-0.000	0.01		-0.021	0.01		0.003	0.01	
Unemployment rate	-0.014	0.00	***	-0.006	0.00		0.008	0.00	**
Nationality - Reference: Belgian									
Non-Belgian EU	-0.064	0.07		-0.087	0.13		-0.043	0.11	
Non-EU	-0.716	0.07	***	-0.313	0.13	**	0.063	0.11	
Education - Reference: Higher secondary									
Primary school	-0.888	0.08	***	-0.107	0.14		0.509	0.11	***
Lower secondary	-0.656	0.05	***	-0.139	0.08	*	0.316	0.07	***
Higher education	0.695	0.05	***	0.095	0.07		-0.208	0.07	***
Other	-0.598	0.17	***	0.098	0.43		0.732	0.27	***
Unknown	0.9178	0.10	***	-0.306	0.11	***	-1.727	0.21	***
Region of residence - Reference: Wallonia									
Flanders	0.418	0.06	***	0.320	0.09	***	0.023	0.08	
Brussels	0.042	0.06		0.187	0.08	**	-0.126	0.08	*
Household position - Reference: Cohabitant									
Head of household	-0.823	0.06	***	-0.211	0.11	*	0.155	0.09	*
Single	-0.103	0.05	**	-0.035	0.08		-0.031	0.07	
Quarter of entry in the spell - Reference: April-May-June									
January-February-March	-0.133	0.05	**	0.093	0.07		0.156	0.07	**
July-August-September	-0.222	0.04	***	0.050	0.06		0.252	0.06	***
October-November-December	-0.180	0.05	***	-0.022	0.07		0.040	0.06	
Firm size - Reference: 500 or more employees or Unknown									
$[1, 20)$ employees	–	–		-0.364	0.06	***	-0.408	0.06	***
$[20, 50)$ employees	–	–		-0.264	0.08	***	-0.436	0.08	***
$[50, 100)$ employees	–	–		-0.172	0.11		-0.196	0.10	**
$[100, 500)$ employees	–	–		-0.078	0.07		-0.273	0.07	***
Sector - Reference: Business services or Unknown									
Agriculture	–	–		0.068	0.22		0.889	0.14	***
Industry & Mining	–	–		-1.327	0.12	***	-0.509	0.11	***
Building & Energy	–	–		-1.090	0.25	***	-0.710	0.26	***
Wholesale & Retail trade	–	–		-1.062	0.07	***	-0.645	0.07	***
Credit & Insurance	–	–		-1.162	0.16	***	-1.405	0.22	***
Other services & Pub. Adm.	–	–		-1.124	0.06	***	-0.696	0.06	***
Decline of unemployment benefits[(a)]									
UI 4	0.017	0.11		–	–		–	–	
UI 3	-0.303	0.20		–	–		–	–	
UI 2	-0.662	0.34	**	–	–		–	–	
UI 1	1.093	0.43	**	–	–		–	–	
# of observations									8,572
# of spells									19,974
# of parameters									125
Log-likelihood									-31,779.2
AIC/# of observations									7.444

Notes: * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
[(a)] The benefits decline variables are defined in subsection 3.2.

ment probabilities and layoffs. This is partly due to the fact that the amount of unemployment insurance depends on the household position (see section 2) and therefore these dummies control for the benefit level. Being head of the household is the position that guarantees the highest amount of unemployment insurance, followed by being single and, at the bottom, cohabitant not in charge of the family. Being head of household or single significantly decreases the (re)employment probability meaning that high benefits decrease the hazard out of unemployment through the opportunity cost of search and leisure. This result is standard in the literature but it should be noted that a structural interpretation cannot be extrapolated from: benefit levels depend on previous earnings and earnings, as time-varying neglected heterogeneity, are an endogenous covariate. Finally, note that the employed who will receive higher benefits in case of job mismatch (singles but above all heads of household) are more likely to end up into unemployment. This result is consistent with the positive correlation between benefit eligibility and employment hazard found in the literature (Christofides and McKenna 1996, Green and Riddell 1997, Baker and Rea 1998).

Finally, as expected according to Moffitt and Nicholson (1982), the coefficient on the closest segment to benefit decline (UI 1) is positive but significant only for women. A change in the opportunity cost of search and leisure when the decline in the amount of unemployment benefits is approached can explain why the probability of an unemployment spell ending rises during the quarter prior to when the amount of unemployment benefits decline.

5.4 Individual Heterogeneity Estimation Results

Following the procedure proposed by Gaure et al. (2007) the discrete distribution function of the random variable $v \equiv [v_{ue}, v_{ee}, v_{eu}]$ has 4 support points for men and 5 support points for women. Therefore, table 7 displays 4 probabilities points and 12 (4×3) estimated heterogeneity points for men and 5 estimated probabilities and 15 (5×3) estimated heterogeneity points for women.

The unobserved heterogeneity plays a fundamental role and, when we take it into account in a flexible way, the inference about duration and lagged duration dependence changes. The probabilities associated to each mass point and the distribution of the heterogeneity points over the support suggest an important diversity of the impact of unobservable characteristics on transition intensities.

Whenever a heterogeneity point was estimated as a large negative number in a model with a given number m of support points, we fixed it to get rid of numerical problems (Gaure et al. 2007) and it is reported in table 7 as

Table 7: Unobserved Heterogeneity Estimation Results

	u-e transition			e-e transition			e-u transition		
	Coeff.	S. E.		Coeff.	S. E.		Coeff.	S. E.	
				Men					
Points of support									
$\ln v_{jk}^1$	-1.273	0.16	***	-2.139	0.31	***	-0.970	0.25	***
$\ln v_{jk}^2$	-0.613	0.27	**	-2.315	0.33	***	-2.727	0.35	***
$\ln v_{jk}^3$	-0.028	0.14		-1.235	0.20	***	-1.760	0.21	***
$\ln v_{jk}^4$	-0.300	0.27		0.098	0.39		0.134	0.42	
Probability mass (logistic transform)				Resulting probabilities					
λ_1	3.319	0.62	***	p_1	0.391				
λ_2	2.889	0.74	***	p_2	0.254				
λ_3	3.183	0.63	***	p_3	0.341				
				p_4	0.014				
	u-e transition			e-e transition			e-u transition		
	Coeff.	S. E.		Coeff.	S. E.		Coeff.	S. E.	
				Women					
Points of support									
$\ln v_{jk}^1$	-1.243	0.16	***	-0.582	0.23	**	-0.488	0.28	*
$\ln v_{jk}^2$	-0.540	0.28	*	-1.020	0.22	***	-2.027	0.30	***
$\ln v_{jk}^3$	0.832	0.25	***	0.142	0.24		-1.771	0.27	***
$\ln v_{jk}^4$	0.098	0.22		-0.952	0.26	***	-1.414	0.26	***
$\ln v_{jk}^5$	1.196	1.20		$-\infty$	–		0.941	3.09	
Probability mass (logistic transform)				Resulting probabilities					
λ_1	5.731	1.28	***	p_1	0.212				
λ_2	6.518	1.37	***	p_2	0.467				
λ_3	4.046	1.33	***	p_3	0.039				
λ_4	6.009	1.29	***	p_4	0.281				
				p_5	0.001				

Notes: * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

negative infinity.[16]

6 Conclusions

This study has been sponsored by the Belgian government in order to deepen the understanding of the mechanisms driving the labour market dynamics of the disadvantaged Belgian youth and to highlight the strategies for their labour market reintegration, employability, and career stability.

The analysis was performed using an administrative dataset on a panel of young school-leavers without any labour market experience and entitled for the first time to unemployment benefits in 1998 after 9 months of job search. Their labour market transitions are followed on a quarterly basis until the end of 2001. A flexible multi-spell multi-state MPH model in a competing-risk framework was estimated especially to understand the effect of previous labour market outcomes on the subsequent labour market performance. The main findings of this study are:

i) The length of the previous job only mildly and not significantly decreases the reemployment probability.

ii) Rather, a job experience generates, *per se*, a positive effect on the unemployment exit rate. By taking into account unobserved heterogeneity and conditional on observed covariates, laid off workers are indeed more likely to find a job than school-leavers.

iii) Conditional on job leaving, shorter-term jobs induce transitions into shorter-term and dead end positions. The effect size on the job to unemployment transition intensity is especially large: one more quarter of tenure in the previous job decreases the current job to unemployment transition intensity by 14.3% for men and 7% for women.

iv) The study could not find any scarring effects on the stability of the subsequent job coming via the unemployment spell duration.

Although this study only partially evaluates the strategies leading to better quality jobs and does not deal with earnings, it can contribute to elucidate what sort of policy interventions may lead the young long-term unemployed to labour market reintegration in terms of job stability, at least in Belgium.

Even if the length of unemployment does not damage the duration of the subsequent job, the importance of leaving the first unemployment spell for the first job experience should not be underestimated. Indeed, we have seen

[16] Individual types characterized by a heterogeneity point for the j-k transition intensity equal to minus infinity make that transition very slowly.

that accepting a job offer, independently on its quality in terms of expected duration, raises the employment probability in case of layoff. Then, policy interventions aimed for speeding up the job-matching process of long-term unemployed school-leavers, for instance by an initial period of wage subsidy specific for these kind of individuals, will lower the aggregate average duration of unemployment also through the post-dismissal signalling channel.

Moreover, by recognising that shorter-term jobs induce transitions into shorter-term and dead end positions, interventions aimed for marginally widening the length of atypical temporary jobs (e.g. fixed-term contracts and contracts for temporary work agencies) can rise the young disadvantaged workers' probability of finding a more stable job at the end of the temporary relationship, reduce the repetition of short-term jobs, and, above all, lower the transition intensity into future dead end positions.

Appendix

A-1 Single-Spell Contribution to the Likelihood Function: the Discrete Time Process as a Continuous Time Model

Assume that we are in a continuous time model and that we are interested in specifying the contribution to the likelihood function of a complete spell s whose origin state is j. Suppose that after a sojourn of t_s quarters in the origin state j, a transition to the destination state k is observed, with $(j,k) \in \mathscr{Z}$. Denote D_{jk} a dummy indicator equal to 1 if a j-k transition is observed and 0 otherwise. We now suppress the set of observable and unobservables characteristics but in what follows we are implicitly conditioning on them.

The contribution to the likelihood function is the unconditional probability of jointly observing the departure from j and the transition to k after a sojourn of t_s quarters in the origin state j, i.e. $\Pr(t_s - 1 \leq T_j < t_s, D_{jk} = 1)$. Since we have quarterly information we do not exactly know when the transition occurs within two consecutive quarters and the best that can be done is to model the probability of observing the departure within two consecutive quarters. This probability can be rewritten as

$$\Pr(T_j \geq t_s - 1)\,\Pr(t_s - 1 \leq T_j < t_s, D_{jk} = 1 | T_j \geq t_s - 1) \tag{A-1}$$

which is the product of the survivor function and of a conditional probability.

The survivor function in state j for $t_s - 1$ quarters is given by

$$\begin{aligned}\Pr(T_j \geq t_s - 1) &= \exp\left\{-\int_0^{t_s-1} \sum_{(j,k)\in\mathscr{J}} \theta_{jk}(\tau)d\tau\right\} \\ &= \exp\left\{-\int_0^1 \sum_{(j,k)\in\mathscr{J}} \theta_{jk}(\tau)d\tau - \int_1^2 \sum_{(j,k)\in\mathscr{J}} \theta_{jk}(\tau)d\tau - \ldots - \int_{t_s-2}^{t_s-1} \sum_{(j,k)\in\mathscr{J}} \theta_{jk}(\tau)d\tau\right\}.\end{aligned}$$

We assume now that the transition intensities are constant within two consecutive quarters since we do not have information about what happens within each interval. Under this assumption we can specify the discrete time process as a continuous time model and the hazard functions can be taken out of the integrals, yielding

$$\begin{aligned}\Pr(T_j \geq t_s - 1) &= \exp\left\{-\sum_{\tau=1}^{t_s-1} \sum_{(j,k)\in\mathscr{J}} \theta_{jk}(\tau)\right\} \\ &= \prod_{\tau=1}^{t_s-1} \exp\left\{-\sum_{(j,k)\in\mathscr{J}} \theta_{jk}(\tau)\right\} = S_j(t_s - 1), \qquad \text{(A-2)}\end{aligned}$$

which is also the contribution to the likelihood function of a right-censored spell as we have seen in equation (5).

The conditional probability in (A-1) can be written as

$$\begin{aligned}\Pr(t_s - 1 \leq T_j < t_s, D_{jk} = 1 | T_j \geq t_s - 1) &= \frac{\Pr(T_j \geq t_s - 1) - \Pr(T_j \geq t_s)}{\Pr(T_j \geq t_s - 1)} \Pr(D_{jk} = 1) \\ = \left[1 - \exp\left\{-\int_{t_s-1}^{t_s} \sum_{(j,k)\in\mathscr{J}} \theta_{jk}(\tau)d\tau\right\}\right] &\times \frac{\int_{t_s-1}^{t_s} \theta_{jk}(\tau)d\tau}{\int_{t_s-1}^{t_s} \sum_{(b,c)\in\mathscr{J}} \theta_{bc}(\tau)d\tau} \qquad \text{(A-3)}\end{aligned}$$

and exploiting again the assumption that the transition intensities are constant within two consecutive quarters we can rewrite (A-3) as

$$\left[1 - \exp\left\{-\sum_{(j,k)\in\mathscr{J}} \theta_{jk}(t_s)\right\}\right] \times \frac{\theta_{jk}(t_s)}{\sum_{(b,c)\in\mathscr{J}} \theta_{bc}(t_s)} \qquad \text{(A-4)}$$

Multiplying (A-2) by (A-4) we get equation (4), i.e. the contribution to the likelihood function of a complete spell s.

A-2 Data Appendix

This appendix reports summary statistics and Kaplan-Meier estimation results not presented in the main text for sake of brevity. Table A-1 shows means and standard deviations of the spell-specific variables until the fifth spell.

Figure A-1 displays Kaplan-Meier estimates of hazard functions of the first un-

Table A-1: Means and Standard Deviations by Gender of Spell-Specific Variables until the Fifth Spell

Spell	2nd		3rd		4th		5th	
Variable	Men	Women	Men	Women	Men	Women	Men	Women
Unemployment rate	.174(.07)	.251(.09)	.168(.07)	.236(.10)	.163(.07)	.227(.10)	.216(.09)	.160(.07)
Age	22.4(2.23)	22.2(2.28)	23.1(2.18)	23.9(2.27)	23.5(2.13)	23.2(2.21)	23.5(2.19)	23.9(2.10)
Quarter of entry in the spell								
January-February-March	.233(.42)	.250(.43)	.286(.45)	.256(.44)	.266(.44)	.269(.44)	.234(.42)	.259(.44)
April-May-June	.158(.36)	.157(.36)	.264(.44)	.270(.44)	.246(.43)	.227(.42)	.237(.43)	.244(.43)
July-August-September	.303(.46)	.301(.46)	.172(.38)	.165(.37)	.279(.45)	.280(.45)	.221(.41)	.220(.41)
October-November-December	.306(.46)	.292(.45)	.279(.45)	.310(.46)	.210(.41)	.223(.42)	.308(.46)	.276(.45)
Household position								
Head of Household	.061(.24)	.059(.24)	.088(.28)	.073(.26)	.087(.28)	.058(.23)	.107(.31)	.064(.25)
Single	.121(.33)	.097(.30)	.170(.38)	.124(.33)	.167(.37)	.142(.35)	.187(.39)	.135(.34)
Cohabitant	.818(.39)	.844(.36)	.742(.44)	.802(.40)	.746(.44)	.800(.40)	.706(.46)	.801(.40)
Firm size								
$[1,20)$ employees	.272(.45)	.254(.44)	.280(.45)	.272(.45)	.241(.43)	.236(.42)	.237(.43)	.265(.44)
$[20,50)$ employees	.063(.24)	.071(.26)	.101(.30)	.096(.29)	.072(.26)	.090(.29)	.105(.31)	.089(.29)
$[50,100)$ employees	.044(.21)	.044(.20)	.057(.23)	.062(.24)	.044(.21)	.047(.21)	.062(.24)	.051(.22)
$[100,500)$ employees	.135(.34)	.142(.35)	.148(.36)	.138(.34)	.142(.35)	.136(.34)	.167(.37)	.113(.32)
500 or more employees	.477(.50)	.485(.50)	.413(.49)	.430(.50)	.495(.50)	.487(.50)	.427(.50)	.482(.50)
Unknown	.009(.10)	.004(.06)	.001(.03)	.004(.06)	.005(.07)	.005(.07)	.006(.08)	.002(.04)
Sector								
Agriculture	.029(.17)	.018(.13)	.013(.11)	.006(.08)	.018(.13)	.009(.01)	.014(.12)	.011(.10)
Industry & Mining	.086(.28)	.039(.19)	.157(.36)	.070(.256)	.095(.29)	.046(.21)	.163(.37)	.100(.30)
Building & Energy	.082(.27)	.011(.10)	.103(.30)	.005(.073)	.064(.25)	.009(.09)	.084(.28)	.007(.09)
Wholesale & Retail trade	.164(.37)	.183(.39)	.192(.39)	.225(.42)	.190(.39)	.186(.39)	.185(.39)	.214(.41)
Credit & Insurance	.014(.12)	.017(.13)	.026(.16)	.037(.19)	.013(.11)	.020(.14)	.024(.15)	.018(.13)
Business services	.411(.49)	.339(.47)	.355(.48)	.311(.46)	.413(.49)	.362(.48)	.378(.49)	.330(.47)
Other services & Public administration	.205(.40)	.390(.49)	.154(.36)	.341(.47)	.201(.40)	.364(.48)	.147(.35)	.318(.40)
Unknown	.009(.09)	.004(.06)	.001(.03)	.002(.04)	.005(.07)	.005(.07)	.002(.04)	.000(.00)

Notes: Standard deviations in parenthesis. Means and standard deviations of spell-specific variables for the first spell are displayed in the main text, table 2.

employment spell and of subsequent unemployment events. The former is drawn from the 4th quarter until the 19th quarter: at the entry date everyone has already spent 3 quarters into unemployment so that minimum and maximum duration of the first unemployment spell are 4 and 19, respectively. The latter is instead depicted from the 1st quarter until the 13th quarter since the minimum and maximum observed duration of subsequent unemployment spells are 1 and 13, respectively. These curves show that the quarterly probability of leaving unemployment is always higher for men during the first unemployment spell, whilst women and men display the same profile during subsequent unemployment events. The overlap between the empirical hazard functions of the first and post-dismissal unemployment spells indicates that individuals seem not to gain in terms of reemployment probability by job experiences. The empirical unemployment hazard rates are non monotonically decreasing during the first 6 quarters of post-dismissal unemployment and only mildly decreasing during the first unemployment spell.

Figure A-1: Kaplan-Meier Unemployment Hazard Functions

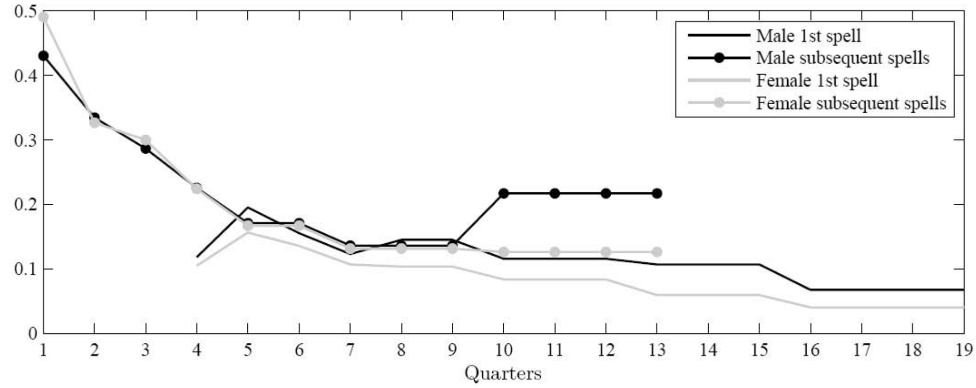
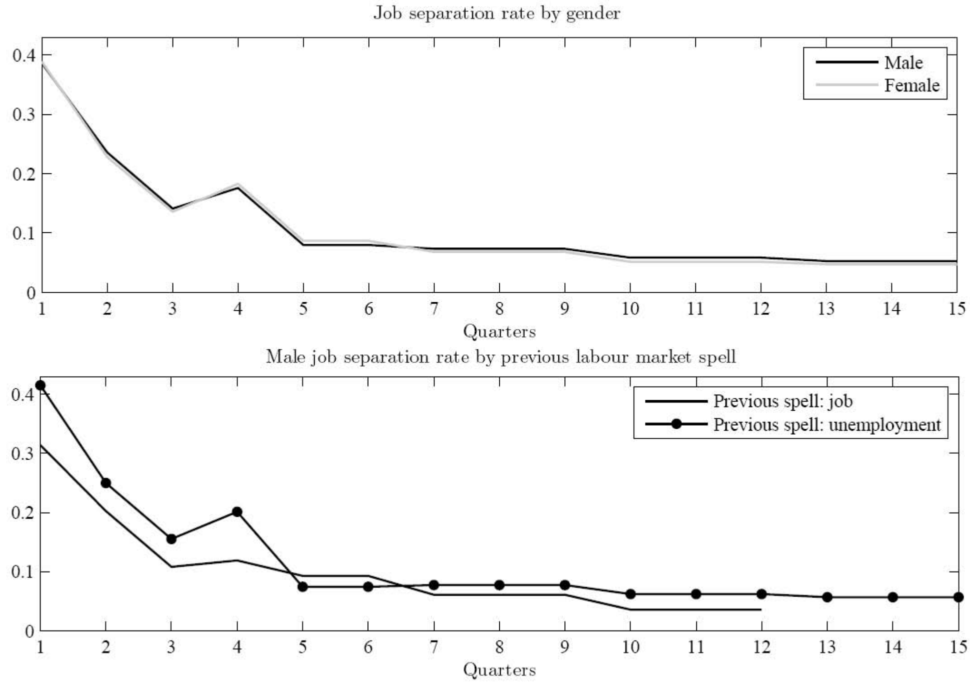


Figure A-2 displays Kaplan-Meier estimates of hazard functions of job experiences by gender and by type of the preceding labour market spell. We can see that men and women share the same level of job separation rate. A job following another job seems to be stabler and less likely to dissolve than a job following an unemployment spell in the first year of the job relationship. After the first year of job tenure, the job separation rate does not depend any longer on the type of the preceding labour market spell. This profile could be due to sorting: jobs that follow an unemployment event could include a larger proportion of higher mobility (less able) workers. This descriptive evidence holds also for women and therefore it is not displayed in the graph.

Figure A-2: Kaplan-Meier Job Hazard Functions



A-3 Further Estimation Results

This appendix displays estimation results not presented in the main text for sake of brevity. Tables A-2, A-3, and A-4 report estimation results of the baseline hazards and the systematic parts from the model that neglects the unobserved heterogeneity.

Table A-2: Estimation Results of the Baseline Hazards without Heterogeneity

Transition	u-e, s=1					e-e			e-u	
Quarters	Coeff.	S.E.		Quarters	Coeff.	S.E.		Coeff.	S.E.	
				Men						
5th	0.552	0.05	***	2nd	-0.179	0.06	***	-0.492	0.06	***
6th	0.375	0.06	***	3rd	-0.476	0.08	***	-1.059	0.08	***
7th	0.173	0.07	**	4th	-0.310	0.08	***	-0.671	0.08	***
8th-9th	0.372	0.06	***	5th-6th	-0.757	0.08	***	-1.833	0.11	***
10th-12th	0.183	0.06	***	7th-9th	-0.982	0.10	***	-1.596	0.11	***
13th-15th	0.139	0.08	*	10th-12th	-1.207	0.16	***	-1.805	0.17	***
16th-19th	-0.279	0.11	**	13th-15th	-1.261	0.36	***	-1.918	0.41	***
Rescaling factor[(a)]	-1.424	0.07	***							
	u-e, s>1									
2nd	-0.255	0.07	***							
3rd	-0.352	0.09	***							
4th	-0.622	0.12	***							
5th-6th	-0.885	0.12	***							
7th-9th	-1.150	0.17	***							
10th-13th	-0.658	0.26	**							
Transition	u-e, s=1					e-e			e-u	
Quarters	Coeff.	S.E.		Quarters	Coeff.	S.E.		Coeff.	S.E.	
				Women						
5th	0.482	0.05	***	2nd	-0.227	0.06	***	-0.589	0.05	***
6th	0.422	0.05	***	3rd	-0.638	0.08	***	-1.081	0.07	***
7th	0.242	0.06	***	4th	-0.452	0.08	***	-0.629	0.07	***
8th-9th	0.272	0.05	***	5th-6th	-0.832	0.08	***	-1.719	0.09	***
10th-12th	0.136	0.06	**	7th-9th	-1.114	0.09	***	-1.800	0.10	***
13th-15th	-0.143	0.08	*	10th-12th	-1.025	0.13	***	-2.751	0.23	***
16th-19th	-0.501	0.11	***	13th-15th	-1.659	0.41	***	-1.866	0.37	***
Rescaling factor[(a)]	-1.614	0.06	***							
	u-e, s>1									
2nd	-0.289	0.07	***							
3rd	-0.273	0.08	***							
4th	-0.602	0.12	***							
5th-6th	-0.825	0.12	***							
7th-9th	-1.014	0.17	***							
10th-13th	-0.959	0.30	***							

Notes: * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. [(a)] See footnote [(a)] of table 4.

Table A-3: Estimation Results of the Systematic Hazards without Heterogeneity – Men

Transition	*u-e*			*e-e*			*e-u*		
Variable	Coeff.	S.E.		Coeff.	S.E.		Coeff.	S.E.	
Age	0.015	0.01	*	0.032	0.01	**	0.022	0.01	*
Unemployment rate	-0.010	0.00	***	0.009	0.01	*	0.003	0.00	
Nationality - Reference: Belgian									
Non-Belgian EU	-0.014	0.06		-0.017	0.11		0.114	0.09	
Non-EU	-0.079	0.06		0.039	0.11		0.158	0.08	*
Education - Reference: Higher secondary									
Primary school	-0.464	0.05	***	0.028	0.09		0.435	0.07	***
Lower secondary	-0.301	0.04	***	0.012	0.06		0.280	0.05	***
Higher education	0.261	0.04	***	0.114	0.07		-0.170	0.07	**
Other	-0.439	0.16	***	-0.149	0.32		0.280	0.19	
Unknown	0.819	0.09	***	-0.324	0.10	***	-2.348	0.31	***
Region of residence - Reference: Wallonia									
Flanders	0.158	0.06	***	0.364	0.09	***	0.086	0.08	
Brussels	0.025	0.05		-0.185	0.08	**	-0.033	0.06	
Household position - Reference: Cohabitant									
Head of household	-0.483	0.05	***	-0.036	0.10		0.268	0.08	***
Single	-0.218	0.04	***	0.096	0.06		0.321	0.06	***
Quarter of entry in the spell - Reference: April-May-June									
January-February-March	0.055	0.05		-0.006	0.07		0.269	0.07	***
July-August-September	-0.090	0.04	**	0.046	0.06		0.205	0.07	***
October-November-December	-0.081	0.04	*	0.004	0.07		0.185	0.07	***
Firm size - Reference: 500 or more employees or Unknown									
$[1, 20)$ employees	–	–		-0.219	0.06	***	-0.326	0.06	***
$[20, 50)$ employees	–	–		-0.242	0.09	***	-0.274	0.09	***
$[50, 100)$ employees	–	–		-0.282	0.11	**	-0.197	0.11	*
$[100, 500)$ employees	–	–		-0.216	0.07	***	-0.224	0.06	***
Sector - Reference: Business services or Unknown									
Agriculture	–	–		-0.595	0.17	***	0.317	0.11	***
Industry & Mining	–	–		-1.089	0.08	***	-0.657	0.08	***
Building & Energy	–	–		-0.796	0.08	***	-0.804	0.09	***
Wholesale & Retail trade	–	–		-1.045	0.07	***	-0.754	0.06	***
Credit & Insurance	–	–		-0.995	0.19	***	-0.987	0.24	***
Other services & Pub. Adm.	–	–		-1.335	0.07	***	-0.694	0.06	***
Decline of unemployment benefits[(a)]									
UI 4	-0.118	0.12		–	–		–	–	
UI 3	0.134	0.18		–	–		–	–	
UI 2	-0.340	0.26		–	–		–	–	
UI 1	0.392	0.36		–	–		–	–	
Constant	-0.534	0.10	***	-1.321	0.17	***	-1.545	0.16	***
# of observations									6,389
# of spells									16,240
# of parameters									110
Log-likelihood									-27,321.0
AIC/# of observations									8.587

Notes: * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. [(a)] The benefits decline variables are defined in subsection 3.2.

Table A-4: Estimation Results of the Systematic Hazards without Heterogeneity – Women

Transition	*u-e*			*e-e*			*e-u*		
Variable	Coeff.	S.E.		Coeff.	S.E.		Coeff.	S.E.	
Age	-0.004	0.01		-0.020	0.01	*	0.018	0.01	
Unemployment rate	-0.010	0.00	***	-0.006	0.00	*	0.004	0.00	
Nationality - Reference: Belgian									
Non-Belgian EU	-0.054	0.05		-0.061	0.11		-0.036	0.10	
Non-EU	-0.635	0.06	***	-0.250	0.12	**	0.048	0.09	
Education - Reference: Higher secondary									
Primary school	-0.755	0.06	***	0.003	0.11		0.396	0.09	***
Lower secondary	-0.565	0.04	***	-0.071	0.07		0.241	0.06	***
Higher education	0.543	0.04	***	0.066	0.06		-0.119	0.06	**
Other	-0.477	0.14	***	0.113	0.37		0.621	0.23	***
Unknown	0.858	0.08	***	-0.289	0.09	***	-1.617	0.20	***
Region of residence - Reference: Wallonia									
Flanders	0.384	0.05	***	0.252	0.08	***	-0.000	0.07	
Brussels	0.023	0.05		0.164	0.07	**	-0.106	0.07	
Household position - Reference: Cohabitant									
Head of household	-0.745	0.05	***	-0.157	0.09	*	0.130	0.07	*
Single	-0.107	0.04	***	-0.043	0.07		-0.024	0.06	
Quarter of entry in the spell - Reference: April-May-June									
January-February-March	-0.117	0.04	***	0.101	0.06		0.127	0.06	**
July-August-September	-0.199	0.04	***	0.059	0.06		0.214	0.06	***
October-November-December	-0.162	0.04	***	-0.019	0.06		0.025	0.06	
Firm size - Reference: 500 or more employees or Unknown									
$[1, 20)$ employees	–	–		-0.343	0.05	***	-0.378	0.05	***
$[20, 50)$ employees	–	–		-0.274	0.08	***	-0.401	0.08	***
$[50, 100)$ employees	–	–		-0.193	0.10	*	-0.192	0.10	**
$[100, 500)$ employees	–	–		-0.090	0.06		-0.265	0.06	***
Sector - Reference: Business services or Unknown									
Agriculture	–	–		0.032	0.21		0.794	0.11	***
Industry & Mining	–	–		-1.264	0.11	***	-0.457	0.10	***
Building & Energy	–	–		-1.069	0.24	***	-0.652	0.24	***
Wholesale & Retail trade	–	–		-0.994	0.06	***	-0.597	0.06	***
Credit & Insurance	–	–		-1.070	0.15	***	-1.277	0.21	***
Other services & Pub. Adm.	–	–		-1.167	0.05	***	-0.618	0.05	***
Decline of unemployment benefits[(a)]									
UI 4	0.108	0.10		–	–		–	–	
UI 3	-0.290	0.20		–	–		–	–	
UI 2	-0.595	0.33	*	–	–		–	–	
UI 1	1.070	0.42	**	–	–		–	–	
Constant	-0.359	0.10	***	-0.645	0.16	***	-1.499	0.16	***
# of observations									8,572
# of spells									19,974
# of parameters									110
Log-likelihood									-31,858.8
AIC/# of observations									7.459

Notes: * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
[(a)] The benefits decline variables are defined in subsection 3.2.

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