Unemployment Duration and the Subsequent Job*

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Abstract

We estimate the joint distribution of unemployment duration, starting wage, and job tenure on the basis of a general and flexible event history model with a correlated Mixed Proportional Hazard (MPH) specification. We incorporate in the model state dependence and show that it is non-parametrically identified without exclusion restrictions. We find that time spent in unemployment pays in terms of longer-lived subsequent jobs through a negative impact on the job-to-job transition intensity and, for men, in terms of higher wages. The impact of unemployment on the starting wage is however moderate: one more year of unemployment increases the male starting wage by 1.6% on average. Female starting wages are instead not affected by unemployment duration. Finally, there is evidence of no significant effect of the starting wage on job tenure.

Keywords: event history analysis, state dependence, wage scarring, unobserved heterogeneity, transition data.
JEL classification codes: C33, C41, J62, J64.

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1 Introduction

Many econometric models are aimed at evaluating the causal effect of the exposure of a set of individuals to some kind of treatment on some future outcomes. In economics, the treatment can be, for instance, training programmes, education, the occurrence of unemployment, or the acceptance of a temporary job. The treatment exposure can be instantaneous or differently prolonged in time. The subsequent outcomes can be, among many others, job finding rates, earnings, or employment stability. The identification of the causal impact provides the economists with the answers to different policy questions and the understanding of policy effects. Heckman (2008) and Imbens and Wooldridge (2008) are recent surveys of econometric developments on causal comparison between outcomes in the presence and in the absence of a treatment.

In this paper we adopt a new perspective and we focus on the identification of the impact of treatment durations (or exposure intensity) on future outcomes. In other words, instead of focusing on what would have been the future outcomes of the treated units if untreated, we deal with the impact of different treatment exposure intensities on treated units' future outcomes. More specifically, the main methodological novelty consists in jointly identifying, on the basis of a general and flexible event history model for school-leavers' labour market outcomes, the causal impact of: the unemployment duration (the treatment duration) on the starting wage and subsequent job tenure (the outcomes); the starting wage (the treatment intensity) on the job duration (the outcome). Our approach basically consists in modelling wages as if they were durations by survival analysis techniques (Donald et al., 2000).

The timing of the realization of our outcome processes is as follows: first, after graduation, unemployment duration is realized; secondly, when and if a job is accepted, a starting wage is observed; lastly, after the acceptance of the wage offer, job duration is realized. Unemployment duration and starting wage are outcomes as well as determinants of later outcomes. Sequential exogeneity of the covariates and lagged outcome variables conditional on unobservables is assumed. We will argue that simultaneous determination of unemployment durations and accepted wages, as predicted by job-search theoretic literature, is not an issue here once we condition upon unobserved heterogeneity fixed at the beginning of the unemployment and job spells. Under the MPH assumption and regressor variation, we prove the joint non-parametric identification of our model by extending the identification results of Honoré (1993) and Horny and Picchio (2009).

This research thereby provides a new estimation strategy to look at the effect of early labour market experiences in terms of two aspects of the quality of the subsequent job, starting wage and job duration. As a matter of fact, this new methodology may find application in many other policy-relevant contexts, like, for instance, the impact of training and its duration on subsequent wages and employment stability.

To our knowledge, only two previous papers face the problem of jointly modelling several labour market outcomes including earnings. First, Mroz and Savage (2006) jointly examine schooling, training, and labour market performances of young men in the US. They find that unemployment has an adverse effect, but since the youth experiencing unemployment get involved in training and work activities, the loss of human capital due to unemployment is mitigated. This generates a catch-up response. The adverse effect of unemployment cannot be fully recovered: a six-month of unemployment at age 22 reduces wages by 8% at age 23 and by 2–3% at ages 30 and 31. Second, Gaure et al. (2008) focus on the impact of labour market policies on unemployment duration, subsequent job duration, and earnings in Norway. They find that job search pays in terms of subsequent starting wage: earnings of the first job match increase by 13% during the first six months of unemployment.

Compared to this prior literature, we claim that our approach is more flexible, for we avoid some parametric assumptions on the form of the wage distribution when estimating it in the presence of covariates. Whereas Mroz and Savage (2006) and Gaure et al. (2008) impose normality of the wage distribution, we flexibly specify the wage hazard rate of the wage distribution so that the estimation procedure boils down to the identification of a wage histogram common to all the individuals which is allowed to vary with observed and unobserved characteristics. This is a kind of transformation of the sample histogram, where the transformation is used to ensure that individual characteristics are introduced in a consistent manner (Donald et al., 2000).

There are several other papers that fit within the context of this research and have sought to identify the effect of unemployment duration just on wages, finding that the longer-term unemployed suffer wage penalties both in the short- and long-term and have difficulties in re-integrating into the labour market (see, e.g., Addison and Portugal, 1989; Pichelmann and Riedel, 1993; Gregg and Tominey, 2005; Gregory and Jukes, 2001; D'Addio et al., 2002; Gangji and Plasman, 2007; Arranz et al., 2005). In contrast to this literature, our methodology provides several advantages consisting in: i) incorporating wage selectivity in the model by appropriately modelling exogenous right censored unemployment durations and endogenous transitions out of the labour force; ii) correcting for selection bias on unobservables in a flexible way; iii) identifying state dependence[1] without the need for instruments

[1] As in Heckman and Borjas (1980) and Doiron and Gørgens (2008), state dependence comprises current and lagged duration dependence. In our framework, the starting wage is in

or exclusion restrictions; iv) solving the simultaneity problem of unemployment duration and subsequent wage. Indeed, as pointed out by Addison and Portugal (1989) and Addison and Blackburn (2000), search-theoretic literature suggests that the unemployment duration and the starting wage are jointly determined. They can both be viewed as a function of the individual specific reservation wage. These advantages nevertheless come at the cost of the MPH assumption, which is required for identification.

Since our identification strategy basically departs from the literature that has dealt with the effects of unemployment on subsequent wages and in order to build a bridge between our method and more conventional estimators, we will start by presenting instrumental variables estimation results of a single-equation linear wage model that incorporates, among the regressors, the endogenous duration of the preceding unemployment spell. Then, we move on to a simplified version of our benchmark hazard-function model, where the identifying assumptions are kept as close as possible to those of the linear wage model, aside from the MPH assumption. We thereby assess whether the MPH assumption might be too strong. Finally, we switch to a more general MPH event history model where the underlying identifying assumptions are relaxed by incorporating in the model the higher mentioned wage selectivity issues (see i)).

Finally, this study is related to the literature on the effect of unemployment duration on subsequent employment duration (see, e.g., Belzil, 2001; Tatsiramos, 2008; Doiron and Gørgens, 2008; Cockx and Picchio, 2009). Within this context, the way we extend a multiple-spell hazard model to jointly model wages is a methodological novelty that allows us to disentangle the impact of unemployment duration on job tenure from that of the starting wage.

The structure of this paper is as follows. The data and sample are described in Section 2. Section 3 illustrates the econometric model and the main identification result. The estimation results are reported and commented in Section 4. Section 5 concludes.

2 The Data

The empirical analysis is conducted by using Belgian administrative records provided by the Crossroads Bank for Social Security (CBSS).[2] The CBSS collects data from the different Belgian Social Insurance institutions and allows to

addition included in the parametrization of the job duration distribution as lagged dependence.

[2]See http://www.ksz.fgov.be/En/CBSS.htm.

reconstruct, on a quarterly basis, the labour market career of the Belgian population. This research is concerned with disadvantaged youth and the impact of unemployment duration on two aspects of job quality: wages and tenure. To this purpose we sampled all Belgian school-leavers, aged between 18 and 25 years, who, in 1998, were still unemployed nine months after graduation. In Belgium, after this "waiting period" of nine months, these school-leavers are entitled to unemployment benefits (UB) and, as a consequence, their information is recorded in the administrative files of the CBSS.[3] In a model with a dynamic structure it is essential to correctly specify the initial conditions. By sampling from a population of school-leavers we drastically simplify initial condition problems in the event history analysis of labour market performances, since this population is completely homogeneous in terms of pre-sampling date labour market experience. Nonetheless, the econometric analysis is somewhat complicated by the fact that all sampled individuals have been unemployed for nine months since graduation. We correct for the selectivity induced by this stock sampling on the basis of a conditional likelihood approach proposed by Ridder (1984). Subsection 3.4 deals with this complication in the construction of the likelihood function.

The sample contains 8,864 women and 6,574 men whose labour market experiences are quarterly observed from the entry moment in 1998 until the end of 2002. Separate estimations are performed for men and women. In the analysis we distinguish three mutually exclusive labour market states occupied at the end of each quarter: unemployed as UB recipient (u), uninterrupted employment by the same employer (e), and an absorbing censoring state (a). This censoring state is accessed if the individual leaves the labour force, enters a training programme or self-employment, returns to school, or is sanctioned and looses the UB eligibility. We consider five possible transitions between these states: ue, ua, eu, ea and, since the data contain a firm indicator, job-to-job transitions ee can be identified as well. As a job is accepted, the starting wage, w, is observed and modelled as well. Job duration is defined as the time spent working for the corresponding employer.

Figure 1 provides an overview of the number of observed labour market transitions, durations, and accepted wages in the data. The post-school unemployment event can be left either for a job, which implies the acceptance of a wage offer, or for the absorbing censoring state. There are instead three reasons for leaving a job: the worker may go back to unemployment, may move directly to another firm, or may enter endogenous censoring. When individu-

[3] Note that the entitlement of school-leavers to UB is atypical, but similar schemes exist in Denmark, Greece, Luxembourg, and Czech Republic although with stricter eligibility criteria (OECD, 2004a).

als move from their first unemployment spell to a job, a wage is observed. At this point, in order to reduce the effects of errors in reported wages and working hours, we consider as wage outliers those employees whose wages lie in the first and last percentiles of the working hours or accepted wage distributions. Wage outliers are exogenously censored at the quarter of job entry and their contribution to the likelihood function will be given only by the component attached to the duration of the post-school unemployment event and the observed transition to a job.

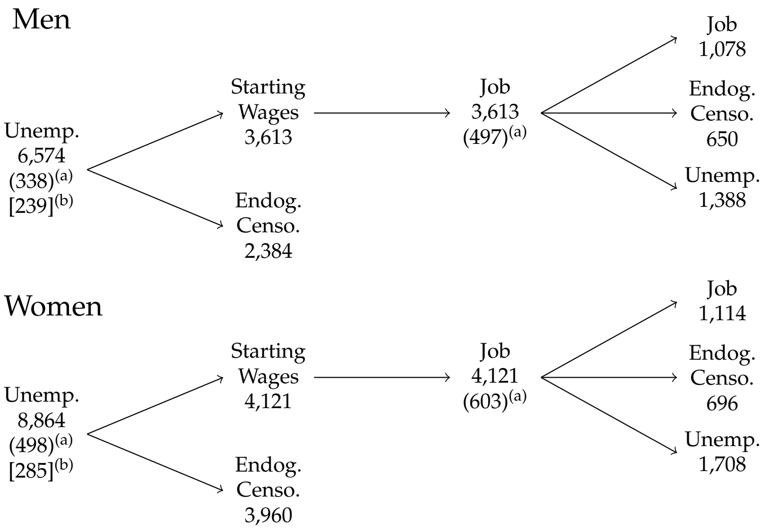
Summary statistics of the outcome variables – post-school unemployment duration, starting wage, and job duration – are reported in Table 1. As the sample consists of long-term unemployed school-leavers, the median duration of the post-school unemployment spell is quite long: 6 quarters for men and 7 for women. The median duration of the first job spell is 2 (3) quarters for men (women). At the end of each quarter spent in a job, we observe quarterly gross wages as well as working hours. Wages displayed in Table 1 are monthly full-time equivalent gross wages in hundreds of euros and in 2000 prices (excluding wage outliers). Young disadvantaged men (women) enter the job market at an average full-time equivalent monthly gross wage of about 1,235€ (1,168€). In Belgium the national minimum monthly gross wage was, in 2000, about 978€.[4] This figure is however the monthly wage that an individual has to be paid on yearly average. Hence, firms can temporarily pay monthly wages below the national minimum wage. Moreover, minimum wages are also bargained at sectoral level using the national minimum wage as reference.[5] In each sector, the minimum wage can vary with age, experience, and the type of job level. As a matter of fact, Figure 2, which plots the estimated kernel density of the accepted full-time equivalent monthly wages, does not show spikes induced by minimum wages. Compared to the normal distribution, the wage distributions are skewed to the left and display excess kurtosis.

Finally, Table 2 displays descriptive statistics of the variables used in the econometric analysis. These can be decomposed into three groups: time-invariant covariates fixed at the sampling date, spell specific variables fixed

[4]Actually, it is the minimum level of earnings, called *revenu minimum mensuel moyen garanti* (RMMMG), that is decided on a national basis. The RMMMG was 1118€ in 2000. It is possible to go from earning to wages by multiplying earnings by 0.875. The RMMMG is a function of age and job experience. The RMMMG reported here and the corresponding minumum wage reported in the text apply to those older than 21 years of age without job experience. Further details on the RMMMG and its conversion to montly gross wages can be found in Moulaert and Verly (2006).

[5]Delegates of employers' and employees' unions of each sector compose the *commission paritaire* of the corresponding sector and bargain minimum wages. In those sectors where the sectoral minimum wage is not bargained, the national minimum wage applies.

Figure 1: Absolute Frequencies of Modelled Labour Market Spells and Wages



[a] In parenthesis are the numbers of right-censored unemployment spells.
[b] In squared brackets the numbers of wage outliers. Wage outliers are those employees with wages lying in the first and last percentiles of the working hours or accepted wage distributions. They are exogenously censored at the quarter in which they enter the job.

Table 1: Summary Statistics of Outcome Variables by Gender

	Mean	S.Dev	Median	Min	Max	Observations
				Men		
Unem. duration (in quarters)[a]	8.21	4.64	6	4	23	6,574
Job duration (in quarters)	4.73	4.81	2	1	18	3,613
Monthly wages (hundreds of €)	12.4	7.9	12.0	2.7	22.3	3,613
				Women		
Unem. duration (in quarters)[a]	8.65	5.00	7	4	23	8,864
Job duration (in quarters)	4.77	4.90	3	1	19	4,121
Monthly wages (hundreds of €)	11.7	2.5	11.3	3.3	21.3	4,121

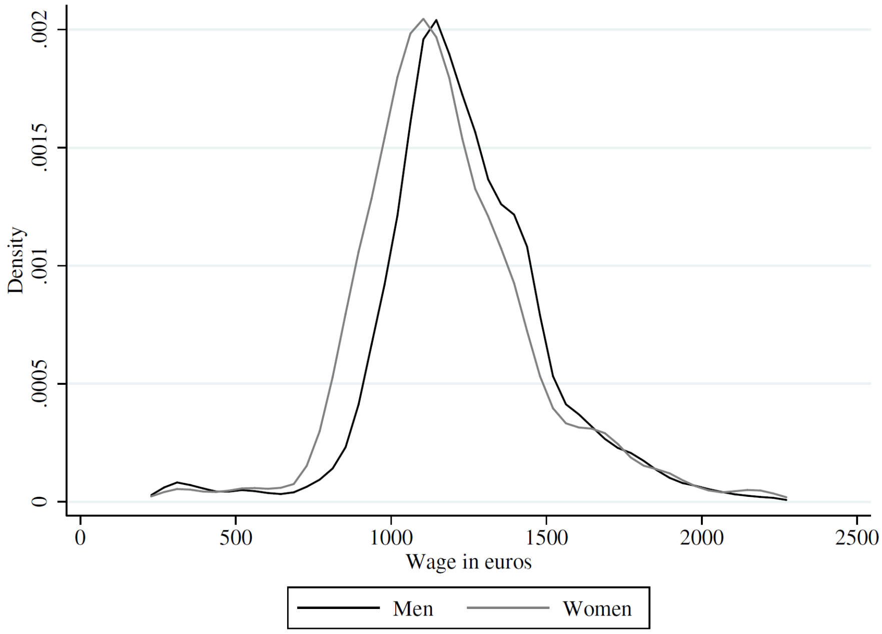
[a] Unemployment duration is counted starting from the graduation calendar date.

Table 2: Summary Statistics of Covariates by Gender

	1st unemployment spell				Entering wages & 1st job spell			
	Men		Women		Men		Women	
	Mean	S.Dev.	Mean	S.Dev.	Mean	S.Dev.	Mean	S.Dev.
	Time-invariant covariates							
Nationality								
Belgian	.892	.311	.880	.325	.895	.306	.895	.306
Non-Belgian UE	.052	.221	.053	.225	.053	.224	.054	.227
Non-UE	.057	.231	.067	.250	.051	.221	.045	.208
Education								
Primary	.122	.327	.079	.270	.100	.300	.047	.212
Lower secondary	.282	.450	.228	.420	.259	.438	.155	.362
Higher secondary	.427	.495	.486	.500	.453	.498	.521	.500
University or more	.127	.333	.174	.379	.138	.344	.229	.420
Unknown	.043	.202	.033	.178	.051	.219	.047	.212
Region of residence								
Flanders	.201	.401	.245	.430	.208	.406	.276	.447
Brussels	.124	.330	.113	.317	.117	.321	.102	.303
Wallonia	.674	.469	.641	.480	.675	.468	.621	.485
Household position								
Head	.077	.266	.107	.309	.063	.244	.062	.242
Single	.134	.340	.101	.302	.119	.324	.098	.297
Cohabitant	.790	.407	.792	.406	.817	.386	.840	.367
	Spell-specific time-variant covariates at spell entry							
Age	20.6	1.95	20.5	1.95	21.5	2.07	21.6	2.10
Quarter of spell entry								
January-February-March	.092	.289	.075	.263	.087	.282	.057	.232
April-May-June	.085	.278	.073	.260	.081	.273	.066	.249
July-August-September	.659	.474	.688	.463	.691	.462	.752	.432
October-November-Dec.	.164	.370	.164	.371	.141	.349	.124	.330
Active labour market policies that depend on unemployment duration								
None	–	–	–	–	.869	.337	.872	.334
Plan à l'embauche 12	–	–	–	–	.067	.251	.060	.237
Plan à l'embauche 24	–	–	–	–	.045	.206	.041	.198
Other policies	–	–	–	–	.019	.136	.027	.162
	Time-variant covariates at spell entry[(a)]							
Local unemployment rate	.187	.068	.273	.082	.174	.070	.250	.092
Number of spells	6,574		8,864		3,613		4,121	

[(a)] The local unemployment rate enters the specification of unemployment and job hazard rates as a time-varying variable. However, it enters the specification of the wage hazard rate as a wage-constant variable, fixed at the moment of acceptance of the corresponding job.

Figure 2: Kernel Estimate of Monthly Wage Density by Gender



at the value attained at the start of the corresponding spell, but varying across spells, and time-varying covariates which values can change every quarter. The first four columns comprise summary statistics of the covariates entering the specification of the unemployment transition intensities, the last four columns deal with the covariates entering the specification of wage and job hazard rates.

Nationality, region of residence, education, and household position dummies are the time-invariant covariates. Since the sample consists of long-term unemployed, sections of the population with a high unemployment risk are more represented in the sample than in the population as a whole: foreigners, lowly schooled youth and, since the unemployment rate in Flanders is much lower, those living in Wallonia and Brussels. The high share of youth living in Wallonia is especially striking: roughly two thirds of the sample lives in Wallonia, whereas only one third of the total Belgian population lives there.

We distinguish between three types of household positions: head of household, single, and cohabitant. These categories determine, together with age, the level of the flat rate UB which the unemployed school-leavers are entitled to after the aforementioned waiting period.[6] The majority of the sampled in-

[6]In 2000, the monthly benefit level varied between 307€ for cohabitants (more than 18

dividuals (79%) is cohabitant, reflecting that most youth is still living at their parents' home.

The set of spell specific explanatory variables contains age and the quarter of spell entry. In a sensitivity analysis, we will augment the benchmark model by a set of dummies controlling for those jobs that are created through targeted active labour market policies which entitle the employer to reductions in social security contributions if the hired worker is long-term unemployed. Indeed they could affect starting wages and, if we do not control for this kind of jobs, it might be that we find spurious effects of the unemployment duration on the starting wage and subsequent job tenure. Most of the job matches (87%) are created without using such labour market policies. In Table 2, *Plan à l'embauche 12* and *Plan à l'embauche 24* refer to two active labour policies that can be used by the employer to hire people unemployed for more than 12 and 24 months, respectively. In the category "Other", that accounts only for 2-3% of the job matches, we included other kind of active labour policies aimed for helping the integration of particularly disadvantaged individuals, for instance people with an unemployment duration longer than 60 months.

Finally, in order to take into account the effect of the fluctuation of the state of the labour market on unemployment and job duration distributions, the local unemployment rate is modelled as a time-varying explanatory variable.[7] Since in Belgium no statistic exists on the local unemployment rate following the standard ILO definition, we rely on a non-standard statistic provided by the Belgian Unemployment Agency (ONEM).[8] This statistic reports the fraction of the population insured against the risk of unemployment (thereby excluding civil servants) which is entitled to UB. This usually results in a higher unemployment rate than the one obtained with the ILO definition. At the sampling date in 1998, the average local unemployment rate for men and women is 18.7% and 27.3%, compared to 7.7% and 11.6% according to the standard ILO definition (http://epp.eurostat.ec.europa.eu).

3 Econometric Modelling

Our approach basically consists in modelling wages as if they were durations by way of survival analysis techniques. In Subsection 3.1 notation and the MPH specification of the unemployment, wage, and job hazard rates are introduced. In Subsection 3.2 model identification is dealt with. Subsection 3.3

years old) not in charge of other members in the household and 790€ for household heads.

[7]It is instead fixed at the moment of job acceptance when it enters the specification of the wage hazard rate.

[8]See http://www.onem.be for more details.

contains a discussion on specification issues of the proportional components of the hazard rates. Subsection 3.4 deals with the derivation of the likelihood function. Finally, in Subsection 3.5 we discuss the advantages and limits of our approach in credibly identifying the causal impact of state dependence.

3.1 Hazard-Function Based Approach

At the beginning of the observation period, unemployment, u, is the common origin state. There are two competing risks of failure, job, e, and endogenous censoring, a. When a job is entered a starting wage is observed and there are three competing risks of failure, job, unemployment, and endogenous censoring.

Consider non-negative random variables $[T_1, D_1, W, T_2, D_2]$ with density function $f(\cdot)$ and cumulative density function $F(\cdot)$. $[T_i, D_i]$, for $i = 1, 2$, is the identified minimum of the ith labour market spell, i.e. $T_1 = \min_{d \in \{ue,ua\}} T_d^*$, $D_1 = \arg\min_{d \in \{ue,ua\}} T_d^*$, $T_2 = \min_{d \in \{ee,eu,ea\}} T_d^*$, and $D_2 = \arg\min_{d \in \{ee,eu,ea\}} T_d^*$. T_d^* is a latent failure time. W is the random accepted wage. The joint density function conditional on observed characteristics, x, and unobserved individual heterogeneity, v, is denoted by $f(t_1, d_1, w, t_2, d_2|x, v)$ and can be rewritten as

$$\begin{aligned} f(t_1, d_1, w, t_2, d_2|x, v) &\equiv f(t_1, d_1|x, v) && (1)\\ &\times f(w|x, v, t_1, d_1) && (2)\\ &\times f(t_2, d_2|x, v, t_1, d_1, w). && (3) \end{aligned}$$

We assume that the latent failure times and starting wages are independent conditional on v, x, and the corresponding lagged dependence. This is a sequential exogeneity assumption that allows us to recover the causal interpretation of the impact of lagged outcomes on future realizations. Moreover, the latent failure times are independent conditional on observed and unobserved characteristics. Thereby, the conditional distributions (1) and (3) factorize in the conditional marginal distributions of each latent failure time. These marginal distributions and the wage distribution are fully characterized by transition intensities and hazard rate which are assumed to be of the MPH form:

$$\begin{aligned} \theta_{uj}(t_1|x, v_{uj}) &= h_{uj}(t_1)\phi_{uj}(x)v_{uj} \quad \text{for } j \in \{e, a\}, && (4)\\ \theta_w(w|x, t_1, v_w) &= h_w(w)\phi_w(x)\pi_w(t_1)v_w \quad \text{if } d_1 = ue && (5)\\ \theta_{ek}(t_2|x, t_1, w, v_{ek}) &= h_{ek}(t_2)\phi_{ek}(x)\pi_{ek}(t_1)\rho_{ek}(w)v_{ek} && (6)\\ & \quad \text{for } k \in \{u, e, a\} \text{ and if } d_1 = ue, \end{aligned}$$

where:

- $(t_1, t_2) \in \mathbb{R}_+^2$ and $w \in (\underline{w}, \infty]$ with $\underline{w} \geq 0$. $\underline{w}$ can be thought of as being a natural lower bound of the accepted wages, exogenous and common to all the individuals. By implication, the wage hazard rate is zero below $\underline{w}$. Following Flinn and Heckman (1982b), a consistent estimator of $\underline{w}$ is the minimum observed wage.[9]
- The $h_{jk}(\cdot)$'s are the baseline hazard functions, common to all the individuals, which will be flexibly specified.
- The $\phi_{jk}(x)$'s are the systematic parts and functions of covariate vectors.
- $\pi_w(t_1)$ and $\pi_{ek}(t_1)$ are the lagged unemployment duration dependence, i.e. the impact of unemployment duration t_1 on the wage hazard rate and the job transition intensities, respectively.
- The $\rho_{ek}(w)$'s capture the impact of the starting wage on subsequent job transition intensities.
- The v_{jk}'s are unobserved individual heterogeneities, non-negative random variables that are distributed independently on x. The cumulative density function of the random vector $v \equiv (v_{ue}, v_{ua}, v_w, v_{ee}, v_{eu}, v_{ea})$ is denoted G. G is allowed to be such that the unobserved heterogeneity components may have mass points at 0, with $\Pr(v > 0) > 0$. As in Abbring (2002) and Abbring and van den Berg (2003a), the model can be defective in the distribution of the latent failure times.

Denote $\Delta_1 \equiv \{ue, ua\}$ the set of pairs of origin-destination states of the first unemployment spell, and $\Delta_2 \equiv \{ee, eu, ea\}$ the set of pairs of origin-destination states of the subsequent job spell. The joint survival function is:

$$\begin{aligned}
\Pr\{T_{ue}^* > t_{ue}, T_{ua}^* > t_{ua}, W > w, T_{ee}^* > t_{ee}, T_{eu}^* > t_{eu}, T_{ea}^* > t_{ea} | x\} \\
= S(t_{ue}, t_{ua}, w, t_{ee}, t_{eu}, t_{ea} | x) \\
= \int_{\Re_+^6} \exp\Big[- \sum_{k \in \Delta_1} H_k(t_k)\phi_k(x)v_k - H_w(w)\phi_w(x)\pi_w(t_1)v_w \\
- \sum_{j \in \Delta_2} H_j(t_j)\phi_j(x)\pi_j(t_1)\rho_j(w)v_j \Big] \mathrm{d}G(v), \quad (7)
\end{aligned}$$

where $H_l(t_l) = \int_0^{t_l} h_l(\tau)\mathrm{d}\tau$, for $l \in (\Delta_1 \cup \Delta_2)$ and $H_w(w) = \int_{\underline{w}}^{w} h_w(s)\mathrm{d}s$.

[9]We implicitly assume that measurement error in wages is not an issue here, for the administrative nature of our data. Moreover, in order to further reduce the possibility of error in wages, we right-censored, at the moment of job acceptance, those workers lying in the first and last percentiles of the working hours or wage distributions (see definition of wage outliers in Section 2).

3.2 Identification

For such a multi-spell MPH duration model one can ask whether the data have anything to say about the distribution of individual heterogeneity, the form of the time dependence, the form of the wage distribution, and finally the lagged dependence. Honoré (1993) and Horny and Picchio (2009) provide partial answers to these questions. The former showed that, under the MPH assumption, regressor variation, and auxiliary assumptions on either the first moment or on the tail behaviour of the mixing distribution, lagged duration dependence is identified in a single risk model. Under similar assumptions, Horny and Picchio (2009) extend Honoré's (1993) proof to competing risks. In what follows, we show that in case of three consecutive spells (i.e. unemployment, starting wage, and job), the specification of the hazard in the third spell is allowed to jointly non-parametrically depend on the outcome of both the first and the second spell. Here, it means that the effects of the unemployment duration and the starting wage are non-parametrically identified in the specification of the job transition intensities. Moreover, model identification requires neither instrumental variables nor exclusion restrictions. The proof of the following theorem is in Appendix A-1.

Theorem 1 *Assume that the joint survivor function of* $(T^*_{ue}, T^*_{ua}, W, T^*_{ee}, T^*_{eu}, T^*_{ea})$ *conditional on* x *is given by (7). Functions* G, H_w, ϕ_w, π_w, (H_l, ϕ_l), $\forall l \in \Delta_1 \cup \Delta_2$, *and* (π_j, ρ_j), $\forall j \in \Delta_2$, *are identified from the distribution of* $(T_1, D_1, W, T_2, D_2)|x$ *under the following assumptions:*

A1 The support χ *of* x *is an open set in* $\Re^n$. *For all* $l \in \Delta_1 \cup \Delta_2 \cup w$, *the* ϕ_l*'s are continuous functions such that* $\{\phi_{ue}(x), \phi_{ua}(x), \phi_w(x), \phi_{ee}(x), \phi_{eu}(x), \phi_{ea}(x)\}$ *contains a non-empty open set in* $\Re^6_+$.

A2 The H_l*'s,* $\forall l \in \Delta_1 \cup \Delta_2 \cup w$, *are non-negative, differentiable, strictly increasing, and not allowed to be* ∞, $\forall (t_1, t_2) \in \Re^2_+$ *and* $w \in (\underline{w}, \infty]$.

A3 Vector v *has non-negative components with distribution function* G *independent on* x *and* $E[v] < \infty$, $E[v_{ue}v_w] < \infty$, *and* $E[v_{ue}v_w v_j] < \infty$ *for all* $j \in \Delta_2$.

A4 For all $l \in \Delta_1 \cup \Delta_2 \cup w$, $\phi_l(x^0) = 1$ *for some fixed* $x^0 \in \chi$ *and* $H_l(t^0) = 1$ *for some fixed* $t^0 \in \Re_+$ *(or* w^0*).*

A5 The ρ_j*'s are non-negative on* $(\underline{w}, \infty]$ *and* $\rho_j(w^{00}) = 1$ *for some fixed* $w^{00} \in (\underline{w}, \infty]$, *for all* $j \in \Delta_2$.

A6 The π_j*'s are non-negative on* $\Re_+$ *and* $\pi_j(t_1^{00}) = 1$ *for some fixed* $t_1^{00} \in \Re_+$, *for all* $j \in \Delta_2 \cup w$.

Our assumptions are in line with the literature. As in Honoré (1993) and Horny and Picchio (2009) and even if multiple labour market spells are observed, identification requires some regressor variation (assumption A1). However, Assumption A1 is much weaker than exclusion restrictions and covariates variation across spell and/or over time, often available in applications, aids satisfaction of Assumption A1.[10] Assumption A3 normalizes the unobserved heterogeneity component by restricting the tail of the frailty distribution to be finite. This is a standard assumption in the literature and it cannot be omitted without loss of identification (Ridder, 1990). The hazard rates and the transition intensities are proportional and therefore innocuous normalizations are required. Assumptions A4, A5, and A6 are normalizations of the systematic parts, integrated baseline hazards, and lagged dependence functions.

The identification analysis is designed for continuous outcomes: continuous duration data and continuous wages. Our data however provide discrete information (on a quarterly basis) on unemployment and job durations. As in Ridder (1990), we would expect that identification with discrete duration data requires more structure on the systematic parts of the unemployment and job transition intensities, like a parametric structure $\phi_l(x) = \exp(x'\beta_l)$ which takes on every value in $\Re_+$. This is left for future investigation.

We do not impose exclusion restrictions on covariates, i.e. we do not require variables that affect the unemployment hazard rate but do not affect the future outcomes, starting wages and job duration. Moreover, we do not rely on instrumental variables to take into account the correlation between lagged outcomes and unobservables in the specification of the subsequent hazard rates. In what follows, we intuitively explain on the basis of which information identification is attained.

While a standard Heckman's (1979) procedure to correct for sample selection bias aggregates into a binary indicator the information on labour market participation, we consider the timing of the dynamic process that, at each point of time, can lead the unemployed either out of the labour force or to a job and therefore to an observed starting wage. As pointed out by Abbring and van der Berg (2003b), the timing of events conveys information that is exploited here to take into account that the observed wage distribution does not represent that of the population.

Workers self-select themselves across the wage distribution according to their individual characteristics and previous unemployment duration. However, for people who left unemployment very soon and in the neighbourhood of the wage lower bound, selection on unobservables has not started yet ex-

[10] Although in the empirical analysis that follows we will use covariates that vary within the unemployment and job spells (the local unemployment rate) and over spells (age and quarter of spell entry), our covariates vector x will not be denoted by time/spell indexes to keep the notation as simple as possible.

erting its effect.[11] Hence, if a difference in the wage hazard rate is observed, it is purely due to differences in the covariates. We identify in this way the impact of the observables on the wage hazard rate. When instead only wages approach the wage lower bound $\underline{w}$, if we observe a difference in the wage hazard rate, it could be due to different covariates and different previous unemployment durations. Since we have already identified the impact of covariates on the wage hazard rate, we can determine how much of the difference is due to different observed characteristics and we can recover and disentangle the pure effect of the previous unemployment duration. Similar intuitive arguments apply for identification of the effect of unemployment duration and starting wages on the job transition intensities.

3.3 Specification Issues

The hazard rate specifications in (4)-(6) encompass unobserved heterogeneity that, if ignored and although uncorrelated to x, may bias the estimation results. There could be indeed some individual characteristics not observed by the econometrician (ability, motivation, responsibility, reservation wage) that are more appealing to employers and that may thereby induce shorter-lasting unemployment spells and subsequent higher wages and longer-lived jobs. In order to avoid a too strong parametric assumption on individual heterogeneity distribution G, v is assumed to be, following Heckman and Singer (1984), a random draw from a discrete distribution function with a finite and, *a priori*, unknown number M of support points. Given the number of possible transitions, we reduced the size of the vector v by assuming $v_{ek} = \alpha_{ek} v_e$ for $k \in \{u, e, a\}$, where v_e is the common factor, independently and identically distributed across individuals. The parameters α_{ek}, for $k \in \{u, e, a\}$, are the loading factors for different types of job destinations. The probabilities associated to the mass points sum to one and, $\forall\, m = 1, \ldots, M$, are denoted by

$$p^m = \Pr(v_{ue} = v_{ue}^m, v_{ua} = v_{ua}^m, v_w = v_w^m, v_e = v_e^m) \equiv \Pr(v = v^m)$$

and specified as logistic transforms:

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

[11] Unobserved heterogeneity instead affects the hazard rates everywhere, while the impact of covariates and the casual impact of lagged unemployment duration are local (Abbring and van der Berg, 2003b).

A predetermined 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).

Misspecification of the baseline hazard functions, or too strict parametric assumptions, is another possible source of biases. The baseline hazards are therefore assumed to be piecewise constant. With regard to the wage hazard rate, the wage support is divided in q intervals $I_r = [w_{r-1}, w_r)$, where $r = 1, \cdots, q$, $w_0 < w_1 < \cdots < w_q$, $w_0 = \underline{w}$, and $w_q = \infty$. We choose the width of the wage baseline segments by dividing the wage support between the 5^{th} and the 95^{th} percentiles of the unconditional wage distributions in 20 equally spaced intervals; we fixed w_1 to the 5% percentile and w_{d-1} to the 95% percentile of the wage distribution. This is somewhat arbitrary but derivation of an optimal rule for segment widths is beyond the scope of this study. Our choice of the number of the baseline segments allowed us to have narrow segment widths to flexibly fit the conditional density function. This sort of specification of the wage distribution indeed implies the estimation of a wage histogram common to all the individuals that is then allowed to vary with observed and unobserved individual characteristics.

As very often done in duration analysis, the systematic parts are specified as follows

$$\phi_l(x) = \exp(x'\beta_l), \quad \text{for } l \in \{ue, ua, w, ee, eu, ea\}.$$

Similarly, we assign the following functional forms to lagged dependence

$$\begin{aligned} \pi_j(t_1) &= \exp(t_1\delta_j), \quad \text{for } j \in \{w, ee, eu, ea\}, \text{ and} \\ \rho_k(w) &= \exp[\ln(w)\gamma_k], \quad \text{for } k \in \{ee, eu, ea\}. \end{aligned}$$

Finally, in the benchmark model, the set of covariates x controlling for the observed heterogeneity is made up of variables that are fixed at the date of entrance in the sample (dummies for nationality, region of residence, education, and household position), fixed at the beginning of the spell (age and quarter of entry in the spell), and time-variant (local unemployment rate). Selectivity bias possibly induced by time-varying factors like fluctuations of the state of the labour market are therefore taken into account by conditioning upon the observed time-path of the local unemployment rate.

3.4 Likelihood Function and Initial Conditions

Since we only observe the labour market state occupied at the end of each quarter, the observed duration data are grouped in discrete time intervals.

However, in order to avoid the dependency of parameters to the time unit of observation (Flinn and Heckman, 1982a), we follow van den Berg and van der Klaauw (2001) and specify the discrete-time process as in a grouped continuous-time model. The contribution to the likelihood function of a complete unemployment spell ending in $j \in \{e, a\}$ is given by[12]

$$L_{iuj}(t_1|x, v_u; \Theta_u) = \frac{\theta_j(t_1|x, v_j)}{\sum_{k\in\Delta_1} \theta_k(t_1|x, v_k)} \big[S_u(t_1 - 1|x, v_u) - S_u(t_1|x, v_u)\big],$$

where

- $v_u \equiv [v_{ue}, v_{ua}]$.
- $S_u(t_1|x, v_u) \equiv \prod_{\tau=1}^{t_1} \exp[-\sum_{k\in\Delta_1} \theta_k(\tau|x, v_k)]$, $\tau \in \mathbb{N}$, is the unemployment survivor function which is fully characterized by transition intensities θ_k, with $k \in \Delta_1$.
- Θ_u is the set of parameters to be estimated determining the contribution to the likelihood function of an unemployment spell.

The contribution to the likelihood of an incomplete unemployment spell is simply given by the unemployment survivor function up to the end of the individual's observation period. Clearly, if the individual has an incomplete unemployment spell, neither starting wages nor job spells are observed and the individual contribution to the likelihood function only comes from the incomplete spell of unemployment.

The contribution to the likelihood function of a complete job spell ending in $j \in \{u, e, a\}$ is given by

$$\begin{aligned} L_{iej}(t_2|x, t_1, w, v_e; \Theta_e) &= \frac{\theta_j(t_2|x, t_1, w, v_e)}{\sum_{k\in\Delta_2} \theta_k(t_2|x, t_1, w, v_e)} \\ &\times \big[S_e(t_2 - 1|x, t_1, w, v_e) - S_e(t_2|x, t_1, w, v_e)\big], \end{aligned}$$

where $S_e(t_2|x, t_1, w, v_e) \equiv \prod_{\tau=1}^{t_2} \exp[-\sum_{k\in\Delta_2} \theta_k(\tau|x, v_e)]$, $\tau \in \mathbb{N}$, is the job survivor function and Θ_e is the set of parameters to be estimated determining the contribution to the likelihood function of a job spell. The contribution to the likelihood of an incomplete job spell is given by the job survivor function up to the end of the observation period.

To construct the contribution to the likelihood function of a wage in the baseline segment $[w_{l-1}, w_l)$, note that the probability of observing a wage in

[12] See appendix A-2 for a more detailed derivation of the unemployment and job spell contributions to the likelihood function.

such a segment is

$$\begin{aligned}\Pr(w_{l-1} \leq W < w_l | x, t_1, v_w) &= S(w_{l-1}|x, t_1, v_w) - S(w_l|x, t_1, v_w) \\ &= L_{iw}(w|x, t_1, v_w),\end{aligned} \tag{8}$$

where $S(w_l|x, t_1, v_w) \equiv \exp[-\int_{\underline{w}}^{w_l} \theta_w(s|x, t_1, v_w)ds]$ is the wage survivor function, i.e. the probability of observing a wage at least as large as the upper limit of the l^{th} segment. Since the wage hazard rate is piecewise constant, the survivor function reduces to $S(w_l|x, t_1, v_w) \equiv \prod_{s=0}^{l} \exp[-\theta_w(w_s|x, t_1, v_w)]$, $s \in \mathbb{N}_0$. Thereby, the difference in survivor functions in (8) is the contribution to the likelihood function of wages lying on the piecewise constant baseline segment $[w_{l-1}, w_l)$. If the wage value is top-coded, i.e. if it is greater than or equal to the 95^{th} percentile of the wage distribution, it is as if it were a right censored duration. The corresponding contribution to the likelihood function is the probability that the wage is larger than or equal to the 95^{th} percentile, $S(w_{d-1=95^{th}}|x, t_1, v_w)$.

In general, the probability of being observed in the labour market state occupied at the sampling date is determined by the history of labour market transitions before this date. Because this history is typically not observed it is usually difficult to derive the correct expression for this probability, unless one makes strong assumptions, such as stationarity. Moreover, since this probability is, in general, a function of the parameters of interest, its misspecification is a source of bias. Here this problem is however simplified, since we know that all sampled individuals entered the labour force nine months before the sampling date. The probability of being observed at the sampling date is therefore given by the joint probability of entering unemployment after graduation and remaining unemployed during the subsequent three quarters. The only parameters of interest involved in this expression are therefore those determining the transition rate from unemployment. The initial conditions problem therefore boils down to a left censoring problem in a single spell framework.

In the derivation of the likelihood we first ignore the initial conditions problem and assume that the sample is drawn at the start of the unemployment spell right after graduation. In a second step, we modify the likelihood to take into account that all workers have already been three quarters unemployed at the sampling date. We correct for selectivity on the basis of a conditional likelihood approach proposed by Ridder (1984) and implemented in Cockx and Picchio (2009).

Individual i's contribution to the likelihood function is given by the product over the individual i's single spell contributions. Let $L_i^m \equiv L_i(\Theta, v^m)$ denote the individual likelihood given that the heterogeneity parameters take on the value v^m, where Θ is the set of other parameters. Exploiting the individual heterogeneity discrete distribution assumption with M support points, the likelihood for individual i is

$$L_i \equiv \sum_{m=1}^{M} p^m L_i^m. \tag{9}$$

We now turn to the modification required to deal with the initial conditions problem. The probability of being observed at the sampling date is given by the joint probability of entering unemployment after graduation and remaining unemployed during the subsequent three quarters. The probability of entry into unemployment can, however, be ignored if we assume that it is proportional in observed and unobserved characteristics (Ridder, 1984). The required modification is therefore just a division of the individual contribution in (9) by the probability of surviving three quarters in unemployment averaged over the unobserved heterogeneity distribution:

$$\mathscr{L}_i \equiv \frac{\sum_{m=1}^{M} p^m L_i^m}{\sum_{m=1}^{M} p^m S_u(3|x, v_u)}. \tag{10}$$

The correction for initial conditions is carried out by the presence of $S_u(3|\cdot)$ in the numerator and denominator of (10): it corrects for different unobserved propensities to leave among different subpopulations and ensures thereby that, conditional on this differential sorting, the impact of observed characteristics remains proportional with duration. Note that the unemployment baseline transition intensities of the first three quarters are not identified, since no-one in the sample leaves unemployment within the first three quarters. We therefore need to assume that these unemployment baseline transition intensities are constant; all the other unemployment baseline transition intensities are estimated in deviation from this constant level.

3.5 Discussion: Estimator's Advantages and Limits

In order to credibly determine the causal impact of lagged labour market outcomes on subsequent performances, it is crucial to have a model that attempts to control for different sources of endogeneity. Previous literature has addressed identification of unemployment scarring effects by way of standard cross-section or panel data techniques. Wage selectivity has been faced by Heckit models and relying on exclusion restrictions (Addison and Portugal, 1989; Ackum, 1991; Arulampalam, 2001; D'Addio et al., 2002; Arranz et al., 2005; Gangji and Plasman, 2007). Correlated time-constant unobserved heterogeneity has been dealt with by time-transforming[13] the log-linear wage equation (Addison and Portugal, 1989; Ackum, 1991; Arulampalam, 2001; Arranz et al., 2005; Gangji and Plasman, 2007) or, in propensity score matching approaches (Gangl, 2006), by relying on the conditional independence assumption. Simultaneity of unemployment duration and subsequent wage, as they are both functions of the reservation wage according to standard search-theoretic literature, was tackled by Addison and Portugal (1989) relying on instrumental variables.

The advantage of our approach consists in the capability of jointly facing and incorporating in the model all these possible sources of bias:

i) We correct, in a flexible way, for selection bias due to unobserved spell-correlated individual heterogeneity. It is well known that the failure to control for (un)observed individual characteristics leads to inconsistent estimates of the structural parameters of interest, in particular of the baseline hazard and, as said, the lagged dependence. The identification theorem ensures that if one imposes the MPH structure on the hazard rates, the multivariate heterogeneity distribution of the unobserved variables is non-parametrically identified together with the structural parameters of the model, including state dependence.

ii) Wage selectivity is addressed by appropriately modelling exogenous right censored unemployment spells and by explicitly specifying an absorbing censoring state (a) the transitions to which (ua and ea) may depend on an unobserved variable that is correlated with the other unobservables (van den Berg and Lindeboom, 1998).

iii) In our sample initial conditions problem boils down to a left censoring problem in single spell framework that is solved by the conditional likelihood approach proposed by Ridder (1984).

iv) As pointed out by Addison and Portugal (1989) and Addison and Blackburn (2000), search-theoretic literature suggests that the starting wage and the duration of unemployment are jointly determined. They can indeed both viewed as a function of the individual specific reservation wage. In our model unemployment and wage hazard rates are allowed to be freely correlated through the unobserved heterogeneity v, which captures also the individual specific reservation wage to the extent to which it is constant. This is supported by the fact that individuals in our sample are entitled to flat rate UB. Nevertheless, the reservation wage may vary over time for other reasons. It may vary with the state of the labour market, but then its time variation would be captured by the local unem-

[13] Fixed effects or first-differencing transformation.

ployment rate, a time-varying covariate included in the model specification. The reservation wage may decline as a consequence of loss in individual skills or of firms using unemployment duration as a signalling device in their hiring strategy. These factors are however captured by the flexible specification of the unemployment baseline transition intensities. Lastly, what could be dangerous is the pace at which the unemployment transition intensities vary between individuals because of an endogenous heterogeneous time-variation of the reservation wage. For instance, high-educated individuals may face a more damaging process of depreciation of human capital or signalling than that of low-educated individuals, generating different reservation wage patterns. If this is so, simultaneity between unemployment and starting wage would be still a problem. In order to test whether this could matter in generating simultaneity bias in disentangling the effect of unemployment duration on the accepted wage, we will carry out a sensitivity analysis in which the baseline unemployment exit rate of high-educated workers is allowed to take a completely different pattern from that of low-educated individuals.

v) Endogeneity of lagged dependence, wage selectivity, and initial conditions are overcome without the need for instrumental variables and exclusion restrictions.

vi) The wage distribution is flexibly specified so that it boils down to a wage histogram common to all the individuals which is allowed to vary with observed and unobserved characteristics. This contrasts to Mroz and Savage (2006) and Gaure et al. (2008) who, in a similar context, impose normality of the wage distribution.

A cost must however be sustained: the MPH assumption is required for model identification. By the way, since in this empirical application we condition on exogenous time-varying covariates, we speculate on the basis of the existing literature (Brinch, 2007; Gaure et al., 2008) that the model is overidentified and that the proportionality assumption might be relaxed. This establishes a link with the identification strategy in panel data dynamic nonlinear models, like in Mroz and Savage (2006), where the information conveyed by the time dimension of exogenous time-varying variables can be exploited to control for endogenous determinants (Bhargava, 1991). Moreover, as in Horny and Picchio (2009), we would expect overidentification when multiple unemployment spells, wages, and job spells are observed. Then, some of the proportionality requirements can be relaxed and variation between spells and within individuals can be exploited to let the baseline hazards, lagged dependence, and individual heterogeneity distribution depend on x. The extension of our empirical approach to a multi-realization framework is in our agenda for future research.

4 Estimation Results

Since our identification strategy basically departs from the literature and is based on the MPH assumption, we will start by estimating in Subsection 4.1 some single-equation linear wage models that incorporate, among the regressors, the duration of the preceding unemployment spell. By instrumental variables (IV) and assuming no wage selectivity due to labour market participation, we identify the effect of unemployment duration on subsequent wages. To establish the link between the identifying assumptions in linear models and those required in a hazard-function framework, we preliminary estimate a simplified version of the model described in Section 3: we ignore the initial conditions problem and labour market spells ending in the absorbing censoring state a are considered as exogenously right censored spells. By doing so, we assume no wage selectivity due to labour market participation, whereas information on the stochastic nature of censoring is incorporated in the model and the MPH assumption is exploited to identify individual heterogeneity distribution and state dependence. In this way, we can realize the consequences of different identifying assumptions on the estimation of the effect of the unemployment duration on the starting wage and whether the MPH assumption is too stringent. In Subsection 4.2 we present the estimation results of the benchmark model described in Section 3, which encompasses wage selectivity and initial conditions issues. Finally, Subsection 4.3 focuses on simulations of the estimated benchmark model, by way of which we check the goodness-of-fit and quantify the impact of longer unemployment durations on the starting wage.

4.1 Preliminary Results Ignoring Wage Selectivity

Consider the following log linear specification of the wage function, which, for expositional convenience, focuses on previous unemployment duration

$$\ln(w_i) = \beta u_i + \delta' x_i + e_i, \tag{11}$$

where w_i is individual i's full-time equivalent quarterly gross wage, u_i is the duration of the preceding unemployment spell, x_i is a set of observed characteristics, and e_i is the error term.

Ordinary least squares estimates of unemployment duration coefficient are likely to be biased because of omitted variables and simultaneity, i.e. failure of the zero correlation assumption between u_i and the error term e_i. Joint determination of unemployment duration and accepted wages is contemplated in job-search theoretic model, where the evolution of reservation and offered wages may feedback into unemployment duration. Estimation results of equation (11), which takes into account of the endogeneity of unemployment duration u_i, are reported in Table 3. In the IV approach we use the local unemployment rate at the moment of school departure as instrument for unemployment duration. It is supposed to be positively correlated to unemployment duration, since it captures the state of the labour market in different areas. In the wage equation we control for the local unemployment rate at job entry. The residual variation of the local unemployment rate at graduation is then a valid excluded instrument to the extent that wages are only directly affected by the current and not by the past labour market state measured by the unemployment rate. In the two-stage least squares (2SLS) approach, overidentification is attained by two further instruments: the number of household members and the number of children younger than six years of age. These further instruments have been traditionally used in the labour supply literature to control for selective participation in the labour force (see, e.g., Mroz, 1987). They are therefore assumed to determine unemployment duration but not to have a direct impact on the starting wage. The F tests for the explanatory power of excluded instruments and the Hansen J statistics support instruments validity. When endogeneity of lagged unemployment duration is corrected for, a significant wage scarring effect for women is found. For men, the impact of unemployment duration on subsequent wages is positive but not significant at the conventional 5% level. Note however that, even if significant, the female wage scarring effect is small in magnitude: one more quarter in unemployment decreases starting wages only by 0.6%.

The last two columns of Table 3 display the average impacts of one more quarter of unemployment on wages estimated from the hazard-function based model (with individual heterogeneity), when initial conditions and transitions to the endogenous censoring state a are ignored. The average impacts and their confidence intervals are computed by simulations, as described in Appendix A-3.2. Consistently with the IV estimation results, unemployment duration does not affect male wages, whereas for women one more quarter in unemployment significantly decreases starting wages by 0.4% on average.[14] The main message is that varying the assumptions for identifying unemployment duration effects on starting wages and relying on the MPH assumption lead to qualitatively and quantitatively similar findings.

[14]The corresponding point estimates of the coefficient entering the wage hazard rate are -0.013, with standard error 0.012, for men and 0.016, with standard error 0.006, for women.

Table 3: The Effect of Unemployment Duration on Wages

	Men	Women	Men	Women	Men	Women	Men	Women
	OLS		IV		2SLS		MPH	
Unemployment duration	.003**	-.001	.006	-.005*	.006	-.005*	.003[a]	-.004**[a]
	(.001)	(.001)	(.004)	(.002)	(.004)	(.002)	[-.002,.007][b]	[-.006,-.001][b]
F test power excluded instruments	–	–	209.4	323.4	71.5	113.9	–	–
Hansen J statistic: p-value	–	–	–	–	.283	.521	–	–
R^2	.143	.287	.144	.286	.144	.286	–	–
Log-likelihood	–	–	–	–	–	–	-29,412.7	-33,905.4
Observations	3,613	4,121	3,613	4,121	3,613	4,121	6,574	8,864

Notes: * Significant at the 5% level; ** significant at the 1% level. In parentheses are heteroskedasticity robust standard errors. In the linear specification of the wage equation we included age, local unemployment rate at job entry, and dummies for nationality, education, region of residence, household position, and quarter of entry in the job. In the instrumental variable (IV) estimation, unemployment duration is instrumented by local unemployment rate at school exit. In the two-stage least squares (2SLS) estimation, the number of members in the household and the number of children younger than six years of age are used as further instruments. The hazard rates of the MPH model are specified as in the benchmark model presented in the next section, apart from initial conditions and exits out of the labour force that are treated here as exogenous. We also tried to include dummies for the year of job acceptance. They were always jointly insignificant and therefore removed from the wage function.

(a) We report the average impact of one more quarter of unemployment on wages, obtained by way of simulations as described in Appendix A-3.2.

(b) Simulated 95% confidence intervals.

4.2 MPH Models Estimation Results

We are primary interested in understanding the effect of the early labour market experience on two main aspects of the job quality: duration and wages. We indeed focus the discussion of the estimation results on the impact of lagged unemployment duration on the subsequent starting wage and job tenure. In addition, we look at the relation between the starting wage and the duration of the corresponding job. The main results discussed in this section are based on the model that: i) takes account of initial conditions; ii) corrects for wage selectivity by explicitly incorporating the transition to the endogenous absorbing censoring state a; iii) controls for selective state dependence induced by unobserved heterogeneity. Since the parameters determining the transition intensities to the absorbing censoring state are not of direct interest, they are reported in Appendix A-4.

The Belgian UB system is very specific in the sense that school-leavers with no labour market experience become eligible to UB after a waiting period of nine months of unemployment. This UB regime is politically and in part justified by a persistent and high level of unemployment rate for youth[15] and by the concern that the quality of the early labour market experiences may affect the subsequent career pattern. UB might indeed subsidize further periods of search increasing the chances of finding jobs that might be more compatible with individual abilities and, thereby, longer lasting and more productive (Burdett, 1979; Marimon and Zilibotti, 1999). However, UB might also work as an incentive to postpone the first job experience generating deterioration of human capital, stigma effects, and consequently negatively affecting future job opportunities (Piore, 1971; Gibbons and Katz, 1991; Lockwood, 1991). The empirical results reported in Table 4 reject the unemployment scarring hypothesis and, in particular for men, are consistent with the former theoretical explanation even if the order of magnitude of the effects is neglegible. In what follows we comment in more details the estimation results of the benchmark model (specification [1] in Table 4). Then, we move on to some sensitivity analyses, whose estimation results are reported in specifications [2]-[6] of Table 4. Finally, we briefly comment on the estimated coefficients of the other explanatory variables.

[15]The European Union Labour Force Survey reported an average unemployment rate of 7.8% over the period 1998–2002 in Belgium. In the same period, the unemployment rate of people younger than 25 years of age was on average 18.9%.

Benchmark model estimation results

Specification [1] informs us that for men one more quarter of unemployment decreases the wage hazard rate by 2.1%. By way of simulations, as we will se in Subsection 4.3, this means that one more year of unemployment increases wages by 1.6% on average. Even if the point estimate is significant, its size is very small. For women, no significant impact of unemployment duration on wages is instead found. These results contrast with Gangji and Plasman's (2007) findings for Belgium: they indeed report that one more year of unemployment implies lower hourly wages of about 10%. The discrepancy might be due to the basically different samples used in the empirical analyses: Gangji and Plasman (2007) selected wage earners that were 18–64 years old, whereas we focus on long-term unemployed school-leavers without any labour market experience. Firstly, the youth might adjust to changes in labour market opportunities through a variety of mechanisms (Card and Lemieux, 2000) that might be systematically different from adults' ones. Secondly, since our sample is made up of the long-term unemployed, the process of loss of skills and the bad signals attached to unemployment may already have worn off their scarring effect during the pre-sampling unemployment period and, therefore, further periods of unemployment do not impose additional damages to the subsequent job quality. This seems to be confirmed by Gaure et al. (2008), who, in a similar hazard model but less flexible in the specification of the wage distribution, find that in Norway a longer unemployment spell pays off in terms of higher wages just during the first six months of unemployment (the wages increase by about 13%); they find no additional wage gains caused by longer unemployment durations.

Institutions may also help in providing an explanation of the almost nil effect of unemployment duration on the subsequent starting wage. In Belgium, wage bargaining occurs every two years at national and sectoral level.[16] Wage bargaining is launched by a national collective agreement that sets the national minimum wage. The national minimum wage is used as the reference of the subsequent bargaining step, which takes place at sectoral level and sets sectoral minimum wages. The national minimum wage is applied in those sectors where wage bargaining does not take place.[17] Such a bargaining regime might compress wages, have an effect on the wage structure through the prices of workers' characteristics, and thereby explain, for youth, the wage rigidity with respect to unemployment duration.

Lastly, different identifying assumptions for wage selectivity and initial conditions may nevertheless partly explain the discrepancy between our find-

[16] In the private sector a third bargaining step could also take place at company level.

[17] In Belgium, collective wage agreements cover about 90% of the workers (OECD, 1997).

ings and most of the previous literature. One of the main advantage of our econometric approach indeed consists in facing wage selectivity, initial conditions, and endogeneity of the lagged outcome variables without requiring and relying on exclusion restrictions. As a matter of fact, when both in linear and wage hazard models we do not control for wage selectivity (as seen in Subsection 4.1), we obtain results more in line with the previous literature: a negative effect of unemployment duration on the starting wage for women and no impact for men. In the previous literature, the failure of the validity assumption for exclusion restrictions could have exacerbated selection biases.

Moving on to the effect of unemployment duration on the subsequent job duration, the point estimates indicate that, both for men and women, one more quarter of unemployment reduces the job-to-job transition intensity by 4% and 6.9%, respectively. Job-to-unemployment transition intensities are instead not affected by the unemployment duration. These findings are in line with those in Cockx and Picchio (2009), where we analyzed, without incorporating wages and using a similar sample, the complete labour market trajectories of Belgian long-term unemployed school-leavers in order to understand whether short-lived jobs can be stepping stones to long-lasting jobs.[18] Similar findings are also reported by Belzil (2001) in Canada and Tatsiramos (2008) in some European countries. Evaluating the impact of UB in terms of their durations respectively on job and employment duration, they find that additional time in unemployment lowers the job and employment hazard rates for UB recipients. We find therefore evidence that a longer job search slightly improves the duration of the subsequent job, as predicted by Burdett (1979) and Marimon and Zilibotti (1999). Nevertheless, unemployment duration affects job duration through a negative impact on job-to-job transition intensities and there could be a trade-off between staying longer in the same job and chances of getting better paid and longer lasting jobs when on-the-job transitions are experienced. For instance, Topel and Ward (1992) found that in the long-term on-the-job trajectories are a source of career development for youth in the US. If this is the case, then a longer unemployment duration may have, by lowering the likelihood of job-to-job transitions, an indirect and negative impact on the long-term wage and career stability profile.

Lastly, the starting wage does not have a significant impact on the job duration. This finding does not support the theoretical prediction in Browning et al. (2007). They designed a model where the access to credit is limited and job seekers can use low-paid jobs as a way to finance consumption during subsequent search for a high-paid job. Cycling between unemployment and

[18]Cockx and Picchio (2009) find that for women unemployment duration has in addition a significant and negative effect on the job to unemployment transition intensity.

Table 4: Lagged Dependence Estimation Results

	[1]		[2]		[3]	
	Men	Women	Men	Women	Men	Women
			Wage hazard rate			
Unemployment duration[(a)]	-.021*	.013	-.030**	.012	-.021*	.011
	(.009)	(.011)	(.010)	(.011)	(.009)	(.011)
			ee transition intensity			
Unemployment duration[(a)]	-.040**	-.069**	-.043**	-.056**	-.040**	-.073**
	(.016)	(.017)	(.016)	(.018)	(.016)	(.016)
Log accepted wages[(b)]	.058	-.107	.044	-.096	.059	-.092
	(.146)	(.158)	(.148)	(.162)	(.146)	(.159)
			eu transition intensity			
Unemployment duration[(a)]	.003	-.002	.013	.002	.003	-.005
	(.012)	(.011)	(.012)	(.011)	(.012)	(.011)
Log accepted wages[(b)]	-.168	.029	-.199	.038	-.165	.040
	(.124)	(.134)	(.124)	(.137)	(.124)	(.134)
Active policies dummies	No		Yes		No	
Skill flexible unemployment baseline hazard	No		No		Yes	
Age flexible wage baseline hazard	No		No		No	
Wage normal distribution	No		No		No	
No initial conditions	No		No		No	
# of parameters	167	168	179	180	172	173
Log-likelihood	-40,155.6	-50,127.2	-40,111.3	-50,063.5	-40,151.1	-50,110.2

	[4]		[5]		[6]	
	Men	Women	Men	Women	Men	Women
			Wage hazard rate			
Unemployment duration[(a)]	-.021*	.010	.000	-.003**	-.027*	-.000
	(.009)	(.011)	(.001)	(.001)	(.013)	(.009)
			ee transition intensity			
Unemployment duration[(a)]	-.039*	-.070**	-.042**	-.066**	-.030	-.058**
	(.016)	(.017)	(.013)	(.013)	(.017)	(.015)
Log accepted wages[(b)]	-.092	-.096	.063	-.166	.046	.004
	(.159)	(.157)	(.143)	(.153)	(.153)	(.176)
			eu transition intensity			
Unemployment duration[(a)]	-.005	-.003	.001	-.001	.009	.005
	(.011)	(.011)	(.010)	(.009)	(.012)	(.010)
Log accepted wages[(b)]	.040	.033	-.153	-.027	-.238	.097
	(.134)	(.133)	(.125)	(.126)	(.123)	(.146)
Active policies dummies	No		No		No	
Skill flexible unemployment baseline hazard	No		No		No	
Age flexible wage baseline hazard	Yes		No		No	
Wage normal distribution	No		Yes		No	
No initial conditions	No		No		Yes	
# of parameters	185	186	146	146	162	162
Log-likelihood	-40,139.9	-50,103.5	-29,370.8	-37,757.7	-40,194.0	-50,105.3

Notes: *Significant at the 5% level; **significant at the 1% level. Standard errors are in parenthesis. Number of observations per each labour market event are those reported in Figure 1.

[(a)] Unemployment duration is in quarters.

[(b)] Log of the full-time equivalent quarterly gross wage at the quarter of job entry.

low-paid jobs arises as a voluntary planned strategy to succeed in obtaining employment at high wages and, as a consequence, low-paid jobs tend to be short-lived jobs. However, our finding is not surprising if one considers the plausible existence of information problems. Then, for example, in order to obtain an efficient allocation of effort on the job, it could emerge a system of deferred payments in which workers get job contracts characterized by low wage at the beginning of the career but steeply rising earnings profile (Lazear, 1979, 1981). This means that it is the type of the bargained wage profile, rather than the starting wage, that might affect job tenure.

Summarizing, we find that time spent in unemployment pays in terms of longer-lived subsequent jobs through a negative impact on the job-to-job transition intensity and, for men, in terms of higher wages. The impact of starting wages on unemployment is however fairly small: one more year of unemployment increases the male starting wage only by 1.6% on average. Female starting wages are instead not affected by unemployment duration. Finally, there is evidence of no significant effect of the starting wage on job tenure.

Sensitivity analyses

In model [2], we augmented the specification of the wage and job hazard rates by dummies indicating whether a job has been created using active labour market policies that entitle the employers to reductions in social contributions if the hired worker is long-term unemployed.[19] If we do not control for this kind of job characteristic, we could find spurious effects of the unemployment duration on the starting wage and subsequent job tenure. Indeed, entitlement to such policies is a function of unemployment duration. If the employer sustains lower costs to hire longer-term unemployed workers entitled to such active policies, the unemployed might be able to bargain higher wages than those of the comparable unemployed not yet eligible to such policies. Once we introduce these dummies in the model, we get estimation results (see specification [2] in Table 4) very much in line with those of the benchmark model.

As anticipated in Subsection 3.5, endogenous heterogeneous time-variation of the reservation wage could be dangerous in generating different patterns of the unemployment exit rate. For instance, high-educated individuals may face a different damaging process of depreciation of human capital or signalling than that of low-educated individuals, generating different reservation wage patterns. In order to test whether this could matter in generating simultane-

[19] More details on eligibility criteria and on descriptive statistics of these dummies can be found in Section 2.

ity bias in disentangling the effect of unemployment duration on the accepted wage, we re-estimated the benchmark model by allowing the baseline unemployment exit rate of high-educated workers (at least a university degree) to take a completely different pattern from that of low-educated individuals. The corresponding estimation results are displayed in specification [3] of Table 4. They are definitively in line with those of the benchmark model. For women, the introduction of such a further degree of flexibility in the specification of the baseline unemployment exit rate improves upon the benchmark model in terms of log-likelihood.[20] It is found that high-educated women do not suffer from negative unemployment duration dependence.

Since in Belgium the national and sectoral minimum wage is higher for workers older than 21 years of age, the wage baseline hazard may differ across age groups in a non-proportional fashion. This is why, in model [4], the wage baseline hazard of workers older than 21 years of age at the moment of job acceptance is allowed to be completely different from that of younger workers. If this is not taken into account, the wage baseline hazard estimation of the benchmark model might be biased and this bias might be transmitted to the other parameters. Therefore, the sensitivity analysis of model [4] tests whether lagged dependence estimation results of model [1] are sensitive to possible misspecification of the wage baseline hazard due to age-varying minimum wage. The estimation results reported in specification [4] of Table 4 clearly point out that this is not the case.

In specification [5], as in Mroz and Savage (2006) and Gaure et al. (2008), we impose normality of the wage distribution.[21] The effect of unemployment duration on wages is again found to be small in magnitude, but qualitatively different: there is no impact for men, whereas for women one more quarter of unemployment significantly reduces wages by about 0.3%. Parametric assumptions on the wage distribution, like the normality assumption, seem to bias the average effect of unemployment duration on wages. The impact of wages and unemployment duration on the subsequent job transition intesities are instead not affected by too strict parametric assumptions on the wage distribution.

In words, identification of the model is attained by looking at those individuals who immediately left unemployment. Indeed, when unemployment

[20] A standard significance test with 5 degrees of freedom to compare the benchmark model and model [3] returned a p-value of 0.000 for women and 0.109 for men.

[21] Thereby, the wage contribution to the likelihood function is now given by

$$L_{iw}(w|x, t_1, v_w) = \frac{1}{\sigma\sqrt{2\pi}} \exp\Big[-\frac{(\ln w - \beta t_1 - \delta' x - v_w)^2}{2\sigma^2} \Big].$$

duration goes to zero, heterogeneity has not yet led to self-selection. Exploiting the fact that the unemployment integrated baseline hazard approaches zero when unemployment duration goes to zero, the systematic part can be identified from the aggregate hazard (Melino and Sueyoshi, 1990). However, our sample is made up of school-leavers that entered unemployment three quarters before the sampling date and we corrected for initial conditions to take into account different unobserved propensities to leave among different subpopulations during the pre-sampling period. It implies that when unemployment duration goes to our observed minimum (three quarters) the integrated baseline hazard is strictly positive. In order to consistently relate the identification analysis to the applied estimation method, we now fix the unemployment baseline hazard to zero at the first three quarters of the pre-sampling unemployment spell and we re-estimate the model (specification [6]). This implies assuming no initial conditions.[22] The corresponding estimation results are in line with those of the benchmark model.

A last sensitivity analysis[23] was conducted to test the robustness of the functional form $\pi_w(t_1)$. We re-estimated the benchmark model by making π_w piecewise continuous spline with two knots, the first one at the second year of unemployment after graduation, the second one at the third year of unemployment. We largely rejected the null hypothesis of slope changes in correspondence of the knots, both for men and women.[24]

Other coefficients

Lastly, we briefly comment on the other estimated coefficients of the benchmark model. The unemployment and job baseline hazards are in line with those in Cockx and Picchio (2009). Table A-1 in Appendix A-4 show negative unemployment duration dependence up to the 7^{th} quarter both for men and women. The baseline unemployment exit rate is roughly constant thereafter for men up to the 16^{th} quarter of unemployment, whereas it continues to decrease for women. The job separation rate declines with tenure, a finding that is consistent with the central facts about working mobility (e.g. Topel and Ward, 1992; Farber, 1999). The spike in the fourth quarter is probably related to the non-renewal of temporary contracts. The transition rate to unemployment declines more and much faster than the job-to-job transition rate. It stabilises after five quarters, whereas the job-to-job transition rate continues

[22]The individual contribution to the likelihood function in (10) would indeed reduce to that in (9)

[23]Not reported in Table 4.

[24]The significance test with 2 degrees of freedom returned a p-value of 0.497 for men and 0.273 for women.

to decline gradually. This means that dismissals essentially occur during the first year, whereas job changes are spread out over a longer time span.

Estimated results of individual heterogeneity distributions are in appendix, at the bottom of Tables A-3–A-6. The estimated probability masses and the location of each mass point suggest an important diversity in the impact of unobserved characteristics on the transition intensities and wage hazard rate. The discrete distribution function of the random variable v is found to have 4 probability masses both for men and women.

Lastly, the estimated coefficients of the full set of covariates are reported in Tables A-3–A-6 in appendix. They are in line with the expectations and, with regard to the duration transition intensities, very close to those found by Cockx and Picchio (2009).

4.3 Simulations

In order to assess the goodness-of-fit of the model and to understand the order of magnitude of the impact of longer unemployment durations on the starting wage, we simulated labour market outcomes by way of the estimation results of the benchmark model.

To construct goodness-of-fit statistics of the model, we use the parameter estimates to simulate 999 labour market histories for each individual in the sample. Replicating the simulation 999 times allows us to construct empirical 95% confidence intervals on the empirical distribution of the duration in each labour market state (u or e), of the transitions to the possible destination states (u, e or a), and of starting wages. The goodness-of-fit can then easily be checked by verifying whether the observed frequencies lie within these confidence intervals. In Appendix A-3.1 we list the steps involved in the simulation procedure.

The first panel of Table 5 contrasts the actual unemployment duration, starting wage, and job duration frequencies with the simulated counterparts and reports simulated confidence intervals. The model fits very well the observed frequencies of the duration and wage distributions. The model however tends to slightly overpredict short unemployment spells and, for men, short-lived jobs.

The second panel of Table 5 reports the fit with respect to the destination states. The model performs very well in predicting the fractions entering a particular destination state. More in details, the model perfectly replicates the fractions of those leaving unemployment for a particular destination both for men and women. With regard to the goodness-of-fit of job destinations, the model is still practically perfect in predicting the fractions of women leaving employment. For men, the fraction of right censored job spells are somewhat underpredicted, but again the size of the misalignment is fairly small.

The simulation procedure to compute the average impact of longer unemployment durations on the starting wage is described in Appendix A-3.2. As expected from the estimation results reported in Table 4, one more quarter in unemployment does not significantly affect, on average, the female accepted wage (-0.2%). A significant wage rise of about 0.4% is instead found for men.[25] When we evaluate the effect of one more year of unemployment we find that the starting wage, on average, significantly increases by 1.6% for men[26] and insignificantly decreases by 0.9% for women.[27] Even if the positive impact of unemployment duration on the male starting wage is significant, its order of magnitude is very small.

5 Conclusions

This research provides a new estimation strategy to look at the effect of early unemployment duration in terms of two aspects of the quality of the subsequent job: starting wage and job duration. We jointly model unemployment duration, starting wage, and job duration distributions on the basis of a general and flexible event history model with a correlated MPH specification. We prove model identification under the MPH assumption and regressor variation. The issues of initial conditions, wage selectivity, and unobserved heterogeneity are also incorporated in the model and addressed in the analysis.

The empirical analysis is performed using a Belgian administrative dataset on young school-leavers without any labour market experience and entitled for the first time to unemployment benefits in 1998, after nine months of job search. Their labour market careers were followed on a quarterly basis until the end of 2002.

We find no cost attached to the duration of the post-school unemployment event for Belgian long-term unemployed school-leavers, neither in terms of the duration of the subsequent job nor in terms of the starting wage. A longer unemployment duration pays in terms of a longer subsequent job tenure through a significant reduction in the job-to-job transition intensity. Longer lasting unemployment spells generate significantly higher starting wages for men, although the impact size is fairly small: one more year of unemployment increases the male starting wage only by 1.6% on average. The female starting

[25] The simulated 95% confidence interval is $[0.04\%, 0.81\%]$.

[26] The simulated 95% confidence interval is $[0.22\%, 2.92\%]$.

[27] The simulated 95% confidence interval is $[-2.54\%, 0.65\%]$.

Table 5: Goodness-of-Fit

	Men				Women			
	Actual frequencies	Simulated frequencies	95% confidence interval		Actual frequencies	Simulated frequencies	95% confidence interval	
Quarters	Unemployment duration distribution							
4	.143	.189	.174	.205	.135	.149	.137	.164
5	**.221**	.238	.221	.253	**.205**	.213	.201	.229
6	**.143**	.142	.129	.153	**.138**	.137	.126	.147
7	**.092**	.084	.075	.095	**.093**	.087	.079	.096
8–9	**.136**	.124	.112	.137	**.134**	.128	.117	.139
10–12	.112	.094	.084	.105	**.114**	.107	.097	.117
13–16	**.075**	.063	.055	.075	**.076**	.073	.065	.081
17–23	**.078**	.067	.059	.079	**.105**	.106	.090	.117
Wage support segments	Starting wage distribution							
$[\underline{w}, w_1)$	**.047**	.047	.037	.056	**.054**	.059	.049	.070
$[w_1, w_3)$	**.063**	.061	.051	.073	**.060**	.065	.054	.076
$[w_3, w_4)$	**.036**	.035	.027	.044	**.041**	.043	.035	.053
$[w_4, w_5)$	**.042**	.042	.033	.052	**.049**	.052	.042	.061
$[w_5, w_6)$	**.049**	.048	.038	.059	**.122**	.126	.112	.141
$[w_6, w_7)$	**.148**	.145	.129	.163	**.064**	.064	.054	.076
$[w_7, w_8)$	**.071**	.070	.059	.082	**.071**	.070	.059	.082
$[w_8, w_9)$	**.056**	.055	.066	.091	**.067**	.066	.056	.077
$[w_9, w_{10})$	**.056**	.056	.045	.066	**.064**	.062	.052	.073
$[w_{10}, w_{11})$	**.101**	.100	.086	.113	**.052**	.051	.042	.062
$[w_{11}, w_{12})$	**.044**	.044	.035	.054	**.091**	.088	.076	.100
$[w_{12}, w_{13})$	**.037**	.036	.028	.045	**.039**	.038	.030	.047
$[w_{13}, w_{14})$	**.047**	.046	.036	.056	**.038**	.036	.029	.045
$[w_{14}, w_{15})$	**.037**	.036	.028	.045	**.029**	.028	.021	.036
$[w_{15}, w_{16})$	**.053**	.053	.043	.065	**.026**	.024	.018	.031
$[w_{16}, w_{17})$	**.011**	.012	.007	.017	**.031**	.028	.022	.036
$[w_{17}, w_{18})$	**.014**	.015	.010	.021	**.011**	.010	.007	.015
$[w_{18}, w_{19})$	**.012**	.013	.008	.018	**.012**	.012	.007	.016
$[w_{19}, w_{21})$	**.021**	.022	.016	.030	**.018**	.017	.012	.023
$[w_{21}, \infty]$	**.057**	.065	.050	.081	**.061**	.061	.048	.079
Quarters	Job duration distribution							
1	.336	.371	.340	.403	**.349**	.353	.326	.383
2	**.167**	.176	.158	.195	**.147**	.147	.131	.163
3	**.086**	.087	.074	.100	**.083**	.082	.071	.094
4	**.090**	.089	.075	.102	**.096**	.096	.083	.109
5–6	**.064**	.062	.051	.074	**.072**	.072	.061	.083
7–9	**.085**	.075	.063	.088	**.073**	.073	.062	.084
10–18	.172	.141	.116	.166	**.180**	.178	.152	.207
Transitions	Transitions from unemployment							
ue	**.586**	.611	.585	.638	**.497**	.497	.469	.524
ua	**.363**	.344	.317	.370	**.447**	.440	.413	.473
Right cens.	**.051**	.045	.039	.052	**.056**	.063	.052	.072
	Transitions from employment							
ee	**.298**	.313	.288	.337	**.270**	.271	.245	.294
eu	**.384**	.410	.383	.439	**.414**	.425	.400	.454
ea	**.180**	.183	.160	.211	**.170**	.174	.152	.202
Right cens.	.138	.094	.075	.112	**.146**	.130	.107	.159

Notes: Actual frequencies lying in the 95% confidence intervals of the simulated frequencies are in bold.

wage is instead not affected by the unemployment duration. Lastly, we find no significant effect of the starting wage on the job duration.

The absence of unemployment scarring on wages was also found by van Ours and Vodopivec (2006) and Gaure et al. (2008). However, our result contrasts with most of the previous literature. The discrepancy might be firstly due to the population under analysis. Since our sample is made up of long-term unemployed school-leavers, the process of loss of skills and the bad signals attached to unemployment may already have worn off their scarring effects during the pre-sampling unemployment period. Therefore, further periods of unemployment do not impose additional damages to the subsequent job quality. Secondly, different identifying assumptions for wage selectivity and initial conditions may partly explain the findings discrepancy. One of the main advantage of our econometric approach indeed consists in facing wage selectivity, initial conditions, and endogeneity of the lagged outcome variables without requiring and relying on exclusion restrictions. In the previous literature, the failure of the validity assumption for exclusion restrictions could have exacerbated selection biases. Thirdly, the Belgian institutional setting, characterized by collective agreements on a pyramidal basis to set minimum wages at national and sectoral level, might partly explain the youth wage rigidity with respect to unemployment duration.

For the future, one intriguing question that remains to be answered is whether youth's chances of having a better career development might be enhanced by accepting, as an alternative to unemployment, low-paid and short-lived jobs. The hazard-function based approach developed in this paper would provide a new and flexible statistical tool to address this issue. However, this approach needs to be qualified. First, only starting wages are incorporated in the analysis and we do not deal with either the wage profile over the labour market career or the within-job wage pattern. Unemployment duration might for instance exert its effect on the workers' wage profile rather than on their starting wages, as well as job tenure might be affected by the wage profile rather than by the starting wage. Secondly, the MPH assumption is needed for identification. This is a limitation that can be overtaken when multiple realizations of the past outcome variables and of the subsequent labour market performances are incorporated in the analysis. This is ground for further research.

A Appendix

A-1 Identification Result

Proof of Theorem 1: From the marginal distribution of $(T_1, D_1, W)|x$ and under Assumptions A1-A5, we can identify H_k, ϕ_k, for $k \in \Delta_1 \cup w$, π_w, and the marginal distribution of $[v_{ue}, v_{ua}, v_w]$ (Horny and Picchio, 2009, see). In what follows we prove identification of job-spell functions. We proceed in sequential steps. In step **(a)**, identification of the job spell systematic parts is shown. Step **(b)** deals with the identification of the unobserved heterogeneity distribution. In step **(c)** the impact of unemployment duration on job transition intensities is identified. Step **(d)** focuses on identification of the impact of starting wages on job transition intensities. Finally, step **(e)** shows identification of the second-spell baseline hazards.

(a) Note that survivor function (7) can be rewritten as

$$\begin{aligned}
&\mathscr{L}_G\{H_{ue}(t_{ue})\phi_{ue}(x), H_{ua}(t_{ua})\phi_{ua}(x), H_w(w)\phi_w(x)\pi_w(t_1), \\
&\quad H_{ee}(t_{ee})\phi_{ee}(x)\pi_{ee}(t_1)\rho_{ee}(w), H_{eu}(t_{eu})\phi_{eu}(x)\pi_{eu}(t_1)\rho_{eu}(w), \\
&\quad\quad H_{ea}(t_{ea})\phi_{ea}(x)\pi_{ea}(t_1)\rho_{ea}(w)\}, \qquad \text{(A-1)}
\end{aligned}$$

where $\mathscr{L}_G$ is the Laplace transform of G.[28]

Denote by $Q_k(t_1, w, t_2|x)$, for $k \in \Delta_2$, the subsurvival probability function. For example, $Q_{ee}(t_1, w, t_2|x)$ is the probability of surviving t_1 time periods in unemployment, accepting wage w, and making a job-to-job transition after t_2 periods on the job. Thereby, a large data set would provide:

$$\begin{aligned}
Q_{ee}(t_1, w, t_2|x) &= \Pr(T^*_{ue} > t_1, T^*_{ua} > T^*_{ue}, W > w, T^*_{ee} > t_2, T^*_{eu} > T^*_{ee}, T^*_{ea} > T^*_{ee}|x), \\
Q_{eu}(t_1, w, t_2|x) &= \Pr(T^*_{ue} > t_1, T^*_{ua} > T^*_{ue}, W > w, T^*_{eu} > t_2, T^*_{ee} > T^*_{eu}, T^*_{ea} > T^*_{eu}|x), \\
Q_{ea}(t_1, w, t_2|x) &= \Pr(T^*_{ue} > t_1, T^*_{ua} > T^*_{ue}, W > w, T^*_{ea} > t_2, T^*_{ee} > T^*_{ea}, T^*_{eu} > T^*_{ea}|x),
\end{aligned}$$

for all $(t_1, t_2, w) \in \Re^2_+ \times (\underline{w}, \infty)$. Then, we can compute the subdensities:

$$\begin{aligned}
Q'''_{ee}(t_1, w, t_2|x) &= \left[\frac{\partial^3 S}{\partial t_{ue}\partial w \partial t_{ee}}\right]_{\substack{t_{ue}=t_{ua}=t_1 \\ t_{ee}=t_{eu}=t_{ea}=t_2}}, \\
Q'''_{eu}(t_1, w, t_2|x) &= \left[\frac{\partial^3 S}{\partial t_{ue}\partial w \partial t_{eu}}\right]_{\substack{t_{ue}=t_{ua}=t_1 \\ t_{ee}=t_{eu}=t_{ea}=t_2}}, \\
Q'''_{ea}(t_1, w, t_2|x) &= \left[\frac{\partial^3 S}{\partial t_{ue}\partial w \partial t_{ea}}\right]_{\substack{t_{ue}=t_{ua}=t_1 \\ t_{ee}=t_{eu}=t_{ea}=t_2}}.
\end{aligned}$$

[28] See, e.g., Lancaster (1990), appendix 2, for properties of the Laplace transform.

Consider Q'''_{ee} and fix x and x^0. As $t_2 \to 0$,

$$\frac{Q'''_{ee}(t_1, w, t_2|x)}{Q'''_{ee}(t_1, w, t_2|x^0)} \to \frac{\phi_{ue}(x)\phi_w(x)\phi_{ee}(x)}{\phi_{ue}(x^0)\phi_w(x^0)\phi_{ee}(x^0)} \times \frac{D_{ee}\mathscr{L}_G\left[H_{ue}(t_1)\phi_{ue}(x), H_{ua}(t_1)\phi_{ua}(x), H_w(w)\phi_w(x)\pi_w(t_1), 0, 0, 0\right]}{D_{ee}\mathscr{L}_G\left[H_{ue}(t_1)\phi_{ue}(x^0), H_{ua}(t_1)\phi_{ua}(x^0), H_w(w)\phi_w(x^0)\pi_w(t_1), 0, 0, 0\right]},$$

where $D_{ee}\mathscr{L}_G() \equiv \partial^3\mathscr{L}_G\{s_{ue}, s_{ua}, s_w, s_{ee}, s_{eu}, s_{ea}\}/\partial s_{ue}\partial s_w\partial s_{ee}$. As $t_1 \to 0$ and $w \to \underline{w}$, $D_{ee}\mathscr{L}_G(.) \to \mathrm{E}(v_{ue}v_wv_{ee}) < \infty$ and identification of ϕ_{ee} is obtained up to a constant, since ϕ_{ue} and ϕ_w have been already identified. Analogously working on Q'''_k, $\forall k \in \Delta_2 - \{ee\}$, yields identification of ϕ_{eu} and ϕ_{ea}.

(b) After imposing $t_{ue} = t_{ua} = t_1^{00}$ and $w = w^{00}$, evaluate the joint survivor function (7) at $t_j = t^0$, $\forall j \in \Delta_2$. We obtain

$$S(t_1^{00}, t_1^{00}, w^{00}, t^0, t^0, t^0) = \mathscr{L}_G\big[H_{ue}(t_1^{00})\phi_{ue}(x), H_{ua}(t_1^{00})\phi_{ua}(x), H_w(w^{00})\phi_w(x), \phi_{ee}(x), \phi_{eu}(x), \phi_{ea}(x)\big]. \quad \text{(A-2)}$$

Survivor $S(t_1^{00}, t_1^{00}, w^{00}, t^0, t^0, t^0)$ is observed. Already identified functions on $\Re^+$ are H_k for each $k \in \Delta_1 \cup w$ and all the systematic parts. By exploiting Assumption A1, we can trace the completely monotone function $\mathscr{L}_G$ on a non-empty open subset of $\Re^6_+$ by appropriately varying x in (A-2).[29] This uniquely identifies it on an non-empty open subset of $\Re^6_+$ by Proposition 1 of Abbring and van den Berg (2003a). As $\mathscr{L}_G$ is real analytic, it can be extended to all of $\Re^6_+$ and uniqueness of the Laplace transform concludes the identification of G.

(c) Pick $x \in \chi$ and as $w \to \underline{w}$ and $t_2 \to 0$ we have

$$\frac{Q'''_{ee}(t_1, w, t_2|x)}{Q'''_{ee}(t_1^{00}, w, t_2|\tilde{x})} \to \frac{h_{ue}(t_1)\pi_w(t_1)\pi_{ee}(t_1)}{h_{ue}(t_1^{00})\pi_w(t_1^{00})\pi_{ee}(t_1^{00})} \times \frac{D_{ee}\mathscr{L}_G\left[H_{ue}(t_1)\phi_{ue}(x), H_{ua}(t_1)\phi_{ua}(x), 0, 0, 0, 0\right]}{D_{ee}\mathscr{L}_G\left[H_{ue}(t_1^{00})\phi_{ue}(x), H_{ua}(t_1^{00})\phi_{ua}(x), 0, 0, 0, 0\right]}, \quad \text{(A-3)}$$

and by letting t_1 vary over $\Re^+$ we can identify π_{ee} up to a constant on all $\Re^+$. By working on Q'''_{eu} and Q'''_{ea} and proceeding in the same way, we can identify π_{eu} and π_{ea}.

[29]Complete monotonicity of the Laplace transform is ensured by the the Hausdorff-Bernstein-Widder Theorem, in Widder (1941, pp. 160).

(d) Pick $x \in \chi$. As $t_1 \to 0$ and $t_2 \to 0$, we get

$$\frac{Q'''_{ee}(t_1, w, t_2|x)}{Q'''_{ee}(t_1, w^{00}, t_2|\tilde{x})} \to \frac{h_w(w)\rho_{ee}(w)}{h_w(w^{00})\rho_{ee}(w^{00})} \frac{D_{ee}\mathscr{L}_G\left[0, 0, H_w(w)\phi_w(x)\pi_w(0), 0, 0, 0\right]}{D_{ee}\mathscr{L}_G\left[0, 0, H_w(w^{00})\phi_w(x)\pi_w(0), 0, 0, 0\right]}. \tag{A-4}$$

By letting w vary over $[\underline{w}, \infty)$ we can identify ρ_{ee} up to a constant on all $[\underline{w}, \infty)$. By working on Q'''_{eu} and Q'''_{ea} and proceeding in the same way, we can identify ρ_{eu} and ρ_{ea}.

(e) To end the proof we need to show identification of the integrated job baseline hazards H_j with $j \in \Delta_2$. For given $(t_1, w) \in \Re_+ \times [\underline{w}, \infty)$ and $x \in \chi$, we solve each Q'''_j in h_j's so that we get a system of three differential equations with initial conditions $H_j(t^0) = 1, \forall j \in \Delta_2$, made up of the following typical equation:

$$h_j\Big(t_2, H_{ee}(t_2), H_{eu}(t_2), H_{ea}(t_2),\Big) = \frac{Q'''_j(t_1, w, t_2|x)}{h_{ue}(t_1)\phi_{ue}(x)h_w(w)\phi_w(x)\pi_w(t_1)\phi_j(x)\pi_j(t_1)\rho_j(w)M_j}, \tag{A-5}$$

where

$$\begin{aligned} M_j =& D_j\mathscr{L}_G\big[H_{ue}(t_1)\phi_{ue}(x), H_{ua}(t_1)\phi_{ua}(x), H_w(w)\phi_w(x)\pi_w(t_1), \\ & H_{ee}(t_2)\phi_{ee}(x)\pi_{ee}(t_1)\rho_{ee}(w), H_{eu}(t_2)\phi_{eu}(x)\pi_{eu}(t_1)\rho_{eu}(w), \\ & H_{ea}(t_2)\phi_{ea}(x)\pi_{ea}(t_1)\rho_{ea}(w)\big], \quad \forall\, j \in \Delta_2. \end{aligned}$$

Set $t_2 = t^0$. The numerators in (A-5) are observed and all the functions entering the denominator of (A-5) have already been identified apart from H_j, $\forall j \in \Delta_2$. We can compute, for all $j \in \Delta_2$, the $h_j(t^0)$'s using the normalization in assumption A4. We can also compute the $H_j(t^0 + \varepsilon)$'s for a sufficiently small ε, and deduce the marginal changes h_j. Plugging them into the system of differential equations (A-5) and solving iteratively, we can uniquely trace out the H_j's on all of $\Re_+$.[30] This completes the proof. ∎

A-2 Deriving the Likelihood Function

Suppose that after a spell of t_1 quarters in unemployment, a transition to a job is observed, i.e. $D_1 = ue$. The contribution to the likelihood function is the unconditional probability of jointly observing the departure from u and the transition to e after a sojourn of t_1 quarters in the origin state u, i.e. $\Pr(t_1 - 1 \leq T_1 < t_1, D_1 = ue)$.[31] Since we have quarterly information we do not exactly know when the transition occurs

[30] Satisfaction of the generalized smoothness Lipschitz continuity ensures the uniqueness of the traced out H_j's (Abbring and van den Berg, 2003a).

[31] We now suppress the set of observed and unobserved characteristics but in what follows we are implicitly conditioning on them.

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

$$\Pr(T_1 \geq t_1 - 1)\Pr(t_1 - 1 \leq T_1 < t_1, D_1 = ue|T_1 \geq t_1 - 1) \tag{A-6}$$

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

The unemployment survivor function for $t_1 - 1$ quarters is given by

$$\begin{aligned}\Pr(T_1 \geq t_1 - 1) &= \exp\left\{-\int_0^{t_1-1}\sum_{k\in\Delta_1}\theta_k(\tau)d\tau\right\}\\ &= \exp\left\{-\int_0^1\sum_{k\in\Delta_1}\theta_k(\tau)d\tau - \int_1^2\sum_{k\in\Delta_1}\theta_k(\tau)d\tau - \ldots - \int_{t_1-2}^{t_1-1}\sum_{k\in\Delta_1}\theta_k(\tau)d\tau\right\}.\end{aligned}$$

We assume now that the transition intensities are constant within two consecutive quarters since we do not have information on 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

$$\begin{aligned}\Pr(T_1 \geq t_1 - 1) &= \exp\left\{-\sum_{\tau=1}^{t_1-1}\sum_{k\in\Delta_1}\theta_k(\tau)\right\}\\ &= \prod_{\tau=1}^{t_1-1}\exp\left\{-\sum_{k\in\Delta_1}\theta_k(\tau)\right\} \equiv S_u(t_1 - 1).\end{aligned} \tag{A-7}$$

The conditional probability in (A-6) can be written as

$$\begin{aligned}&\Pr\left(t_1 - 1 \leq T_1 < t_1, D_1 = ue|T_1 \geq t_1 - 1\right)\\ &= \frac{\int_{t_1-1}^{t_1}\theta_{ue}(\tau)\exp\left\{-\int_0^{\tau}\sum_{k\in\Delta_1}\theta_k(s)ds\right\}d\tau}{\exp\left\{-\int_0^{t_1-1}\sum_{k\in\Delta_1}\theta_k(s)ds\right\}}\end{aligned} \tag{A-8}$$

and exploiting again the assumption that the transition intensities are constant within two consecutive quarters, equation (A-8) can be rewritten, following Cockx (1997), as

$$\left[1 - \exp\left\{-\sum_{k\in\Delta_1}\theta_k(t_1)\right\}\right] \times \frac{\theta_{ue}(t_1)}{\sum_{b\in\Delta_1}\theta_b(t_1)}. \tag{A-9}$$

Multiplying (A-7) by (A-9) and reintroducing the set of observed and observed characteristics yield the following contribution to the likelihood function of a complete unemployment spell ending in a job

$$L_{iu}(t_1|x, v_{ue}, v_{ua}; \Theta_u) = \frac{\theta_{ue}(t_1|x, v_{ue}, v_{ua})}{\sum_{b\in\Delta_1} \theta_b(t_1|x, v_{ue}, v_{ua})} \times \left[S_u(t_1-1|x, v_{ue}, v_{ua}) - S_u(t_1|x, v_{ue}, v_{ua})\right] \qquad \text{(A-10)}$$

where Θ_u is the set of parameters when the origin state is u. The contribution to the likelihood function of a complete unemployment spell ending in the endogenous censoring state, a, is given by replacing θ_{ue} with θ_{ua} in the numerator of equation (A-10). Job spells contribution to the likelihood function are similarly derived.

A-3 The Simulation Procedures

This Appendix describes the steps involved in both the simulation to construct the goodness-of-fit statistics and the one to understand the order of magnitude of the impact of longer unemployment durations on the starting wage reported in Subsection 4.3.

A-3.1 The Simulation with regard to the Goodness-of-Fit

We first discuss a complication induced by the stock sampling of the data. This affects the specification of the distribution of unobserved heterogeneity from which vector-values are drawn and assigned to each sampled individual at the start of each simulation loop. Since all sampled individuals have already been unemployed for three quarters at the start of the observation period, the distribution of unobserved heterogeneity must be modified along the lines of the adjustment of the likelihood function. This means that the probability p_i^m that individual i is of type m and is therefore assigned the vector of location points $\hat{v}^m \equiv [\hat{v}_{ue}^m, \hat{v}_{ua}^m, \hat{v}_w^m, \hat{v}_e^m]$ for $m = 1, \ldots, \widehat{M}$ can be estimated by

$$\hat{p}_i^m = \frac{\widehat{S}_u(3|x_i; \widehat{\Theta}_u, \hat{v}_u^m)\hat{p}^m}{\sum_{r=1}^{\widehat{M}} \widehat{S}_u(3|x_i; \widehat{\Theta}_u, \hat{v}_u^m)\hat{p}^m}, \qquad \text{(A-11)}$$

where $\widehat{M} = 4$ for men and women. Observe that this distribution depends on the values of the observed explanatory variables at the sampling date.

The simulation then proceeds according to the following steps:

1. Draw a vector of parameter estimates assuming that the estimator is Normally distributed around the point estimates with a variance-covariance matrix equal to the estimated one.
2. Assign to each individual the value of the observed explanatory variables at the sampling date and a vector of unobserved characteristics drawn with the probability as given in Equation (A-11).

3. Simulate the transition from unemployment (u) to employment (e) and the endogenous censoring state (a) by a sequence of quarterly transition lotteries starting from the 4^{th} quarter, which corresponds to the start of the observation period. These transition lotteries are based on the empirical counterparts of the probability of leaving state u for k ($k = e, a$), conditional on surviving in state u until the end of the previous quarter. Their form is given by Equation (A-9). In this process, the local unemployment rate, which is time-varying, is adjusted to the new value at the beginning of each quarter.
4. If a transition to the censoring state a occurs, the simulation for that individual is halted. If there is a transition to employment, assign new values to the unemployment rate and the spell specific time-varying variables. The age and quarter of spell entry of each individual are assigned the values as reported at the calendar time corresponding to the quarter of entry in the simulated job spell.
5. Simulate the starting wage by a sequence of lotteries for each wage baseline segments in increasing order, until we observe that a wage is accepted. These wage baseline segments lotteries are based on the empirical counterparts of the following conditional probability

$$\Pr(w_{l-1} \leq W < w_l | W \geq w_{l-1}, x, t_1, v_w) = 1 - \exp[-\theta_w(w_l | x, t_1, v_w)].$$

6. Simulate the transitions from the employment state according to a similar sequence of quarterly lotteries as described for the unemployment state in point 3.
7. The simulation procedure is halted once the end of the observation period is reached, i.e. in December 2002, 17 to 20 quarters after the sampling date.
8. Repeat for each individual points 1 to 7 999 times to obtain 999 independent labour market realizations for each sampled individual.

A-3.2 The Simulation with regard to the Impact of Longer Unemployment Durations on Wages

The simulation procedure to compute the average impact on wages of increasing by one quarter or by one year the unemployment duration goes as follows:

1. Simulate the labour market history for all individuals in the sample as in points 1 to 7 of Appendix A-3.1.
2. For each individual who makes a simulated transition in employment, we resimulate twice the wage: the first time by increasing by one quarter the previous unemployment duration; the second time by increasing by one year the previous unemployment duration (everything else is kept constant).
3. Compute the differences in the simulated wages before and after the increase in the lagged unemployment duration.

4. Repeat points 1 to 3 999 times to obtain 999 independent realizations of the average wage impact of increasing by one quarter and by one year the lagged unemployment duration.
5. Finally, sort the 999 realizations of the average wage impact of increasing unemployment duration and construct confidence intervals.[32]

A-4 Further Estimation Results

This appendix displays estimation results of the benchmark model not presented in the main text for the sake of brevity. Tables A-1 and A-2 comprise the point estimates of the parameters of all the baseline hazards. Finally, Tables A-3–A-6 report all the parameter estimates of the systematic parts and individual heterogeneity discrete distribution of the benchmark model. The estimation results not reported in this paper for the sake of brevity can be asked to the authors.

[32] We follow Davidson and Mackinnon (2004, § 4.6) to construct confidence intervals.

Table A-1: Benchmark Model Estimation Results of the Duration Baseline Hazards by Gender

Transition	ue		ua			ee		eu		ea	
Quarters	Coeff.	S.E.	Coeff.	S.E.	Quarters	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Men											
5th	-.140***	.053	.444***	.078	2nd	.267***	.092	-.381***	.073	-.033	.126
6th	-.233***	.062	.568***	.090	3rd	-.634***	.117	-1.022***	.105	-.050	.141
7th	-.386***	.073	.513***	.102	4th	-.307**	.117	-.581***	.100	.052	.154
8-9th	-.080	.067	.403***	.107	5-6th	-.767***	.122	-2.008***	.154	-.513***	.168
10-12th	-.123	.077	.624***	.126	7-9th	-.870***	.128	-1.472***	.126	-.645***	.181
13-16th	-.102	.096	.958***	.163	10-18th	-1.102***	.135	-1.893***	.151	-.679***	.194
17-23rd	-.868***	.140	.832***	.202							
Women											
5th	-.122**	.050	.502***	.066	2nd	-.255***	.091	-.678***	.070	-.367***	.127
6th	-.089	.060	.444***	.081	3rd	-.781***	.118	-1.241***	.096	-.125	.128
7th	-.236***	.071	.385***	.095	4th	-.454***	.113	-.515***	.079	-.328**	.148
8-9th	-.123*	.072	.359***	.110	5-6th	-.908***	.115	-1.744***	.110	-.576***	.140
10-12th	-.195**	.085	.430***	.137	7-9th	-1.108***	.121	-1.795***	.110	-1.037***	.159
13-16th	-.418***	.108	.477***	.172	10-18th	-1.181***	.112	-2.641***	.146	-.939***	.148
17-23rd	-.850***	.142	.614***	.204							

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

Table A-2: Benchmark Model Estimation Results of the Wage Baseline Hazard by Gender

Log wage support segments	Coeff.	S.E.	Coeff.	S.E.
	Men		Women	
$[w_1, w_3)$	.339***	.104	.180*	.093
$[w_3, w_4)$	-.162	.120	-.142	.104
$[w_4, w_5)$	.060	.113	.110	.099
$[w_5, w_6)$	.269**	.109	1.169***	.083
$[w_6, w_7)$	1.525***	.090	.690***	.095
$[w_7, w_8)$	.980***	.102	.939***	.094
$[w_8, w_9)$	.878***	.107	1.055***	.098
$[w_9, w_{10})$	1.015***	.107	1.200***	.102
$[w_{10}, w_{11})$	1.796***	.097	1.203***	.109
$[w_{11}, w_{12})$	1.190***	.115	2.066***	.106
$[w_{12}, w_{13})$	1.154***	.121	1.539***	.127
$[w_{13}, w_{14})$	1.581***	.115	1.734***	.132
$[w_{14}, w_{15})$	1.565***	.123	1.719***	.140
$[w_{15}, w_{16})$	2.247***	.115	1.817***	.151
$[w_{16}, w_{17})$	.968***	.185	2.273***	.147
$[w_{17}, w_{18})$	1.346***	.167	1.492***	.195
$[w_{18}, w_{19})$	1.365***	.183	1.771***	.189
$[w_{19}, w_{21})$	2.158***	.151	2.403***	.173

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

Table A-3: Benchmark Model Estimation Results of Systematic Parts and Individual Heterogeneity Distribution – Men

Transition	ue		w		ee		eu	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Time-invariant covariates								
Nationality - Reference: Belgian								
Non-Belgian EU	.034	.123	-.093	.085	.342**	.136	.106	.126
Non EU	-.050	.122	.028	.084	.203	.168	.188	.132
Education - Reference: Higher secondary								
Primary school	-1.110***	.112	.148*	.092	-.168	.149	.386***	.110
Lower secondary	-.884***	.093	.087	.071	-.154	.102	.123**	.084
Higher education	.812***	.121	-.774***	.085	.189	.114	.018	.108
Unknown	-.709***	.136	-.056	.132	-.954***	.188	-2.902***	.375
Region of residence - Reference: Wallonia								
Flanders	.728***	.112	-.164**	.088	.522***	.148	.246*	.131
Brussels	.234**	.090	.258***	.057	-.022	.113	-.012	.093
Household position - Reference: Cohabitant								
Head of household	-1.056***	.095	-.099	.092	-.160	.150	-.042	.119
Single	-.233***	.083	.065	.058	.084	.109	.351***	.083
Time-variant spell-specific covariates								
Age	-.036**	.017	-.005	.012	-.028	.022	-.034*	.019
Quarter of entry in the spell - Reference: April-May-June								
Janu.-Febr.-March	-.109	.097	-.065	.049	-.280***	.089	-.087	.076
July-August-Sept.	-.136	.094	.082	.057	-.280***	.100	-.300***	.090
Octo.-Nove.-Dece.	-.265***	.080	-.113***	.047	-.251***	.079	-.279***	.071
Time-variant covariates								
Local unem. rate	-1.718***	.561	-.255	.445	.690	.771	.904	.670
Individual heterogeneity distribution – $M = 4$								
Support points								
$\ln v^1_{jk}$	-.010	.156	-2.845***	.155	-1.583***	.199		
$\ln v^2_{jk}$	-4.444***	.587	-3.045***	.703	3.568	–	α_{eu}	
$\ln v^3_{jk}$	-1.241***	.152	-3.035***	.172	-2.211***	.152	.847***	.130
$\ln v^4_{jk}$	-1.866***	.175	-2.452***	.179	-1.972***	.255		
Probability masses (logistic transform)					Resulting probabilities			
λ_1	1.425***	.146			p_1	.476		
λ_2	-3.012***	.417			p_2	.006		
λ_3	1.261**	.160			p_3	.404		
λ_4	.000	–			p_4	.114		

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

Table A-4: Continuing Table A-3

Transition	ua		ja	
Variable	Coeff.	S.E.	Coeff.	S.E.
Time-invariant covariates				
Nationality - Reference: Belgian				
Non-Belgian EU	-.119	.164	-.005	.205
Non EU	-.514***	.178	.342*	.183
Education - Reference: Higher secondary				
Primary school	-.082	.159	.676***	.172
Lower secondary	-.080	.116	.292**	.142
Higher education	.566***	.135	-.013	.179
Unknown	2.708***	.258	-1.022***	.293
Region of residence - Reference: Wallonia				
Flanders	.700***	.166	.338*	.186
Brussels	.204	.123	.112	.143
Household position - Reference: Cohabitant				
Head of household	.159	.161	-.207	.190
Single	-.080	.112	.194	.134
Time-variant spell-specific covariates				
Age	-.065***	.024	.010	.028
Quarter of entry in the spell - Reference: April-May-June				
January-February-March	.420***	.153	.059	.116
July-August-September	.396**	.155	-.124	.132
October-November-December	.634***	.113	-.095	.110
Time-variant covariates				
Local unemployment rate	-2.902***	.742	-.530	.952
Lagged dependence				
Unemployment duration	–	–	-.005	.019
Log accepted wages	–	–	-.202	.187
Individual heterogeneity distribution – $M = 4$				
Support points				
$\ln v_{jk}^1$	-5.559***	.323		
$\ln v_{jk}^2$	-3.555***	.423	α_{ea}	
$\ln v_{jk}^3$	-1.415***	.200	1.648***	.219
$\ln v_{jk}^4$	-3.349***	.248		

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

Table A-5: Benchmark Model Estimation Results of Systematic Parts and Individual Heterogeneity Distribution – Women

Transition	ue		w		ee		eu	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Time-invariant covariates								
Nationality - Reference: Belgian								
Non-Belgian EU	-.023	.089	.104	.084	-.008	.147	.075	.108
Non EU	-.832***	.092	.174	.106	-.136	.166	.054	.121
Education - Reference: Higher secondary								
Primary school	-1.016***	.097	.149	.120	.065	.195	.481***	.113
Lower secondary	-.736***	.064	.270***	.069	-.029	.109	.327***	.072
Higher education	.958***	.100	-.960***	.096	.080	.113	-.171*	.091
Unknown	1.303***	.167	-.368***	.136	-.365**	.173	-1.530***	.219
Region of residence - Reference: Wallonia								
Flanders	.557***	.087	-.038	.080	.332***	.122	.105	.096
Brussels	.161**	.073	-.065	.071	.168	.113	-.194**	.094
Household position - Reference: Cohabitant								
Head of household	-.944***	.082	.036	.087	-.139	.156	.076	.102
Single	-.015	.069	-.121*	.065	-.006	.108	.071	.085
Time-variant spell-specific covariates								
Age	-.001	.013	-.089***	.013	.024	.021	-.025	.017
Quarter of entry in the spell - Reference: April-May-June								
Janu.-Febr.-March	-.215**	.085	-.016	.052	-.139	.086	-.161**	.066
July-August-Sept.	-.060	.081	.113*	.058	-.192*	.099	-.245***	.077
Octo.-Nove.-Dece.	-.265***	.062	-.130***	.047	-.153*	.079	-.285***	.066
Time-variant covariates								
Local unem. rate	-2.003***	.352	.629*	.337	-.370	.544	1.664***	.349
Individual heterogeneity distribution – $M = 4$								
Support points								
$\ln v^1_{jk}$	-.733***	.193	-3.273***	.194	-2.026***	.155		
$\ln v^2_{jk}$	-1.929***	.172	-2.374***	.193	-1.913***	.212	α_{eu}	
$\ln v^3_{jk}$	-.950***	.174	-2.456***	.207	-1.953***	.193	.664***	.106
$\ln v^4_{jk}$	-3.717***	.803	-3.386***	.983	.243	1.348		
Probability masses (logistic transform)					Resulting probabilities			
λ_1	3.634***	.954			p_1	.187		
λ_2	4.024***	.764			p_2	.277		
λ_3	4.676***	.851			p_3	.531		
λ_4	.000	–			p_4	.005		

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

Table A-6: Continuing Table A-5

Transition	ua		ja	
Variable	Coeff.	S.E.	Coeff.	S.E.
Time-invariant covariates				
Nationality - Reference: Belgian				
Non-Belgian EU	-.186**	.090	.020	.178
Non EU	-.372***	.096	.011	.200
Education - Reference: Higher secondary				
Primary school	-.254***	.088	.664***	.180
Lower secondary	-.020	.062	.115	.124
Higher education	.536***	.099	-.121	.155
Unknown	.876***	.191	-1.170***	.288
Region of residence - Reference: Wallonia				
Flanders	.354***	.092	-.317**	.148
Brussels	.087	.070	-.076	.136
Household position - Reference: Cohabitant				
Head of household	-.258***	.077	.316**	.157
Single	.050	.067	.285**	.122
Time-variant spell-specific covariates				
Age	-.032***	.012	.004	.026
Quarter of entry in the spell - Reference: April-May-June				
January-February-March	.295***	.078	-.033	.107
July-August-September	.066	.075	-.060	.121
October-November-December	.373***	.061	-.118	.104
Time-variant covariates				
Local unemployment rate	-1.513***	.362	-.402	.656
Lagged dependence				
Unemployment duration	–	–	-.001	.021
Log accepted wages	–	–	.016	.206
Individual heterogeneity distribution – $M = 4$				
Support points				
$\ln v_{jk}^1$	-3.474***	.689		
$\ln v_{jk}^2$	-2.720***	.206	α_{ea}	
$\ln v_{jk}^3$	-1.707***	.211	1.410***	.188
$\ln v_{jk}^4$	-2.928***	.499		

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

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