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SCARRING EFFECTS OF REMAINING UNEMPLOYED FOR LONG-TERM UNEMPLOYED SCHOOL-LEAVERS

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Scarring Effects of Remaining Unemployed for Long-Term Unemployed School-Leavers*

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Abstract

This study investigates whether and to what extent further unemployment experience for youths who are already long-term unemployed imposes a penalty on subsequent labor market outcomes. We propose a flexible method for analyzing the effect on wages aside of transitions from unemployment and employment within a multivariate duration model that controls for selection on observables and unobservables. We find that prolonging unemployment drastically decreases the chances of finding employment, but hardly affects the quality of subsequent employment. The analysis suggests that negative duration dependence in the job finding rate is induced by negative signaling and not by human capital depreciation.

Keywords: scarring effect of unemployment duration, employment quality, wage in multivariate duration model, selectivity.
JEL classification codes: C33, C41, J62, J64.

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1 Introduction

The high incidence of youth unemployment concerns the general public and many policy makers. It is not however unusual that youth experiences more unemployment at the start of their professional career, since workers are typically searching for an adequate job match in this phase of the career. This search process induces high job turnover, possibly with intervening spells of unemployment. The high incidence of unemployment for youth may therefore be only temporary. If so, youth unemployment would dissolve automatically without any intervention, so that no specific measures for fighting youth unemployment are needed. Moreover, even if an unemployment experience leads to a penalty in terms of employability or wages, this penalty could gradually fade away by a "catch up" response induced by a higher intensity of on-the-job training for workers with more past unemployment experience. Mroz and Savage (2006) indeed find evidence for such a catch up response for American youth. However, they also report that unemployment experienced as long ago as ten years continues to adversely affect earnings despite the catch-up response. The existence of persistent earnings penalties of unemployment experienced early in the career is confirmed in other studies both in the U.S.[1] and in Europe.[2] There is therefore quite firm evidence that policies aiming at the prevention of youth unemployment yield long-lasting effects which should be taken into account when judging their merit.

What happens, however, if preventive policy does not succeed and youth becomes long-term unemployed? Are there long-run costs associated to further delays in work experience once one is already deprived of it for some time? Is further unemployment experience beyond a certain period of inactivity no longer harmful? This study investigates these questions for youth in Belgium who remained more than nine months unemployed after leaving school. More insight into this issue provides valuable information for the design of curative policy for long-term unemployed youth, i.e. whether it remains urgent to fight unemployment.

We analyse an administrative panel of 14,660 youngsters who in 1998 were still unemployed nine months after graduating from school and for whom the quarterly labor market histories, including the gross monthly starting wages, could be constructed for up to five years later until the end of 2002. We analyse these data by means of a multivariate duration model explicitly allowing for lagged state and duration dependence to capture the scarring effects of remaining unemployed and explicitly integrating the analysis of wages within this framework.

[1] See e.g. Ellwood (1982) and Kletzer and Fairlie (2003).

[2] See e.g. Arulampalam (2001), Gregg (2001), Gregg and Tominey (2005), and Gartell (2009). Ackum (1991) finds no significant effect on earnings of Swedish youth. Gregg (2001) reports only minor persistence for women. Gangji and Plasman (2007) find substantial scarring effects of unemployment incidence and duration on prime aged workers in Belgium. However, they do not study the specific impacts on youth early in the career.

An advantage of this modeling approach is that it identifies the sources of the scarring effect of unemployment duration, if any. Unemployment duration can affect labor market outcomes directly and indirectly. The direct effect is through negative duration dependence in the transition from unemployment to employment or through its lagged impact on the starting wage and on the subsequent employment stability. The indirect effect is through the employment experience that is forgone, influencing thereby both the duration of subsequent (un)employment spells and the wage of subsequent employment spells. Insight into these sources is not only important to formulate policy advice but also to shed light on which of the competing theories on labor market dynamics, such as human capital or signaling, are relevant in explaining the labor market transitions of disadvantaged youth at the start of their labor market career.

From a methodological point of view it is key to distinguish between true and spurious lagged (un)employment duration dependence induced by the correlation with unobserved individual propensities to remain (un)employed. This is further complicated by the fact that the effect of lagged duration can only be identified for individuals for whom one observes a transition to the subsequent labor market state of interest. This leads to the so-called "sample selectivity problem" (Heckman, 1979). We explicitly control for selectivity that is induced by time invariant unobserved factors.

A number of researchers have followed a similar methodology to study the effect of unemployment insurance, i.e. the level and duration of benefit receipt, on the duration of subsequent employment spells[3] or to analyse the effect of lagged state and duration dependence on labor market transitions.[4] A few researchers[5] have integrated the effect on wages within this framework, but assumed that wages are lognormally distributed conditional on covariates. This research contributes to the literature by proposing a flexible estimator of the wage distribution and by modeling it as a function of piecewise constant baseline hazards which are shifted proportionally by (un)observed explanatory variables. Donald et al. (2000) proposed this approach to construct a flexible estimator of wage distributions that are functions of a large number of observed covariates. We extend this framework by allowing for dependence on unobserved covariates and by integrating it within a model of multiple states and spells including lagged occurrence and duration dependence.[6]

The organization of the paper is as follows. Section 2 describes the data. Section 3 presents the econometric model. The estimation results are reported and commented in Section 4. Section 5 shows goodness-of-fit statistics and simulations aimed at quantifying the effect, in terms of employment stability, of delaying the first employment experience of one or two years. Section 6 concludes.

[3] Belzil (1995, 2001); Jurajda (2002); Tatsiramos (2009).

[4] Böheim and Taylor (2002); Doiron and Gørgens (2008); Cockx and Picchio (2011).

[5] Bratberg and Nilsen (2000); Gaure et al. (2008); McCall and Chi (2008).

[6] Arni et al. (2009) have used our framework to estimate the impact of benefit sanctions on earnings.

2 The Data

The empirical analysis is conducted on administrative records gathered by the Crossroads Bank for Social Security (CBSS).[7] The CBSS merges data from the different Belgian Social Insurance institutions and allows thereby to construct the quarterly labor market history of all Belgian workers. The data include real gross quarterly earnings[8] and the fraction of a full time worked in the quarter. The analysis is based on the gross monthly full-time equivalent (FTE) starting wage defined as one third of the ratio of these two variables as measured in the quarter right after a transition to employment.[9]

The sample retains all Belgian youth, 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, school-leavers are entitled, without any time limit, to flat rate unemployment benefits (UB) and, as a consequence, show up for the first time in the administrative records of the CBSS. This selection results in a sample of 8,433 women and 6,227 men. By sampling from a population of school-leavers the initial conditions problem present in dynamic models with lagged endogenous variables is drastically simplified, since nobody in the sample had any labor market experience prior to the sampling date. Nevertheless, the fact that all sampled individuals have been unemployed for nine months since graduation leads to a problem of left truncation. In Subsection 3.3 we discuss how we deal with this complication.

The quarterly (un)employment history of these workers can be reconstructed for a period of (maximum) five years, from the beginning of 1998 until the end of 2002. In the analysis we distinguish between three mutually exclusive labor market states occupied at the end of each quarter: unemployed as UB recipient (u), employed (not necessarily by the same employer) (e), and an absorbing censoring state (a). This censoring state is accessed if the individual leaves the labor force, enters a training program or self-employment, returns to school, or is sanctioned and loses the UB eligibility.[10] These states define four potential transitions: ue, ua, eu, and ea. The starting wage (w) is modelled as an intermediate labor market state that is realized before the start of each employment spell: it is as if the transition ue were decomposed in two intermediate transitions, uw and we. Over the five years time window, (un)employment spells and starting wages can be observed repeatedly for the same individual. For the sake of limiting the computational complexity, we restrict the empirical analysis to maximum two realizations per individual.

Table 1 reports, by gender, descriptive statistics on the endogenous variables: unemployment and employment durations, transitions from the origin states, the FTE monthly

[7] See http://www.ksz.fgov.be/en/international/home/index.html.

[8] Wages are deflated by the consumer price index of January 2001.

[9] To accommodate for measurement errors observations are exogenously right censored at the start of the employment spell if the fraction of working time or the starting wage is contained in the first or last percentiles of the corresponding distributions.

[10] We model the exit to these states as absorbing to reduce computational complexity.

Table 1: Descriptive Statistics of the Endogenous Variables by Gender

a. Men	Origin state			
	1st unemployment spell	2nd unemployment spell	1st employment spell	2nd employment spell
Observed spell duration (quarters)				
Average per person	5.3[a]	3.1	6.5	5.2
Number of spells				
Total	6,277	1,689	3,505	1,047
Right censored on December 31, 2002	333	200	934	366
Absorbing censoring state	2,291	397	848	212
Uncensored	3,653	1,092	1,723	469
Duration percentiles (quarters)				
25th	5	1	2	1
50th	7	2	4	4
75th	10	4	11	8
FTE gross monthly starting wages (€)				
Mean	–	–	1,256	1,286
Standard Deviation	–	–	261	254
Skewness			0.038	0.002
Kurtosis			5.253	4.715
Median	–	–	1,217	1,250
Entitled to high UB[b]				
Fraction of spells	0	0.208	–	–

b. Women	Origin state			
	1st unemployment spell	2nd unemployment spell	1st employment spell	2nd employment spell
Observed spell duration (quarters)				
Average per person	5.8[a]	2.8	7.3	5.3
Number of spells				
Total	8,433	2,012	3,983	1,229
Right censored on December 31, 2002	490	186	1,018	415
Absorbing censoring state	3,768	555	932	219
Uncensored	4,175	1,271	2,033	595
Duration percentiles (quarters)				
25th	5	1	2	2
50th	7	2	4	4
75th	11	3	11	9
FTE gross monthly starting wages (€)				
Mean	–	–	1,188	1,231
Standard Deviation	–	–	257	255
Skewness			0.487	0.571
Kurtosis	–	–	4.902	4.512
Median	–	–	1,150	1,217
Entitled to high UB[b]				
Fraction of spells	0	0.156	–	–

[a] When computing these figures, we do not count the elapsed unemployment duration (3 quarters) at the sampling date.
[b] One is entitled to a higher UB if employed for more than one year.

wage at the beginning of the corresponding employment spell and the fraction of spells entitled to a higher UB. The last mentioned variable is endogenous, since the entitlement to higher UB depends on the duration of the previous employment spell and on the previous wage. If one is uninterruptedly employed for more than one year, then the UB is no longer flat rate but proportional (limited by a floor and a cap) to the wage earned in the previous job. In the econometric analysis we take this into account by including an indicator variable that is equal to one if the UB is high and zero otherwise. Since we sample from a population of school-leavers, there is no one eligible to high UB in the first unemployment spell and only a minority in the second unemployment spell (21% for men and 16% for women).

The median duration for the first unemployment spell is much higher than the one of the second unemployment spell, respectively 7 and 2 quarters, both for men and for women. This is a consequence of the sample selection rule requiring school-leavers to be unemployed 9 months before showing up for the first time in the administrative records of the CBSS. The median duration of the 1st and 2nd employment spells is one year for both genders.

The average wage of the first employment spell is about €1,256 for men and €1,188 for women. The wage at the beginning of the second employment spell is somewhat higher, €1,286 for men and €1,231 for women. Compared to the Normal distribution the wage distributions display excess kurtosis and especially the female wage distributions are skewed to the right. In spite of a minimum wage legislation in Belgium, the distributions do not exhibit a spike at the lower bound. There are several explanations for this. First, in Belgium the national minimum wage is a lower bound for minimum wages bargained at the sectoral level by type of worker (blue or white collar). This means that the national minimum only applies for the minority of workers who are not covered by a sectoral minimum. Second, the national minimum depends on the age of the worker and on job tenure.[11] Finally, the national minimum needs not to be satisfied at each instant, but only on average within a year.[12]

Table 2 displays descriptive statistics of the covariates used in the econometric analysis. These can be decomposed into two groups: time-invariant covariates fixed at the sampling date and time-varying covariates changing every quarter. The first four columns comprise summary statistics computed for individuals entering an unemployment spell.

[11]The baseline national minimum concerns workers older than 21 years without any tenure. The minimum for younger workers falls gradually to 70% of the baseline for 16 year olds. The baseline is 2.75% and 4% higher if tenure (beyond the age of 21) exceeds 6 and 12 months, respectively.

[12]This latter feature also complicates the comparison with the wage data we use in this analysis, since our wage data do not comprise some sector and firm specific bonuses, like the end-of-year bonus, which are included instead in the national minimum (Moulaert and Verly, 2006). As a rule of thumb, one therefore should multiply the minimum wage by 0.875 to make the minimum wage comparable to our wage data. In 2000, the converted national minimum wage for an 18 year old worker attained 802€. In the sample 2.6% of male and female starting wages are below this minimum.

Table 2: Summary Statistics of Covariates by Gender

	1st unemployment spell				1st employment spell and wage			
	Men		Women		Men		Women	
	Mean	S.Dev.	Mean	S.Dev.	Mean	S.Dev.	Mean	S.Dev.
	Time-invariant covariates at sample entry							
Age at sample entry	20.49	1.96	20.37	1.96	20.37	1.96	20.58	1.95
Kids $[0, 3)$ years old	.032	.176	.100	.300	.030	.170	.056	.237
Nationality								
Belgian	.888	.315	.875	.331	.889	.314	.897	.304
Non-Belgian UE	.053	.225	.054	.227	.057	.231	.056	.229
Non-UE	.058	.234	.071	.256	.054	.226	.047	.212
Education								
Primary or none	.127	.333	.083	.276	.104	.306	.049	.217
Lower secondary	.295	.456	.233	.423	.271	.445	.162	.368
Higher secondary	.446	.497	.503	.504	.479	.499	.548	.498
Post secondary	.132	.339	.180	.384	.145	.352	.241	.428
Region of residence								
Flanders	.167	.373	.218	.413	.168	.374	.238	.426
Brussels	.129	.336	.120	.324	.123	.328	.108	.310
Wallonia	.703	.457	.663	.473	.709	.454	.654	.476
Household position								
Head	.079	.270	.114	.317	.065	.247	.064	.246
Single	.137	.344	.105	.307	.122	.327	.101	.301
Cohabitant	.783	.412	.781	.414	.813	.390	.835	.371
	Time-variant covariates at spell entry[(a)]							
District unemployment rate	.187	.069	.270	.087	.182	.067	.259	.089
Regional GDP growth	.022	.009	.023	.010	.023	.013	.024	.013
Quarterly indicators								
January-February-March	.085	.279	.073	.260	.236	.424	.250	.433
April-May-June	.655	.475	.695	.461	.161	.368	.168	.374
July-August-September	.165	.371	.158	.365	.302	.459	.301	.459
October-November-Dec.	.094	.292	.075	.263	.302	.459	.282	.282

[(a)] We report here figures at unemployment and employment spell entry, although the district unemployment rate, the regional GDP variation, and quarterly indicators enter the specification of unemployment and employment hazard rates as a time-varying variable. They enter the specification of the wage hazard rate as a wage-constant variable, fixed at the beginning of the corresponding employment event.

The last four columns deal with summary statistics computed for individuals entering an employment spell.

Age, presence in the household of kids younger than 3 years, nationality, education, region of residence, and household position dummies are the time-invariant covariates. At the moment of entry into the sample, individuals are about 20.5 years old. Since the sample consists of long-term unemployed, sections of the population with high unemployment risk are more represented than in the population as a whole: foreigners, low educated 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: more than two thirds of the sample has the residence in Wallonia, whereas only one third of the total Belgian population lives in this region. At the sampling date 10% of women and 3% of men reside in households with children younger than 3 years old. This suggests that family constraints induced by the presence of children younger than 3 years, the age at which children in Belgium generally start going to kindergarten, influences the employment probability more negatively for women than for men.

We distinguish between three types of household positions: head of household, single, and cohabitant. A head of household lives together with children or adults with an income below a certain threshold. One is a "cohabitant" if the income of at least one other household member exceeds this threshold and a "single" if living alone. These categories determine, together with age, the level of the flat rate UB to which the unemployed school-leavers are entitled after the aforementioned waiting period of nine months.[13] The majority of the sampled individuals (78%) are cohabitants. This reflects their young age: the majority still lives with their parents.

The transitions in and out of unemployment are likely to depend on local labor market and business cycle conditions. In the time window under analysis, the real GDP growth rate increased steadily from 1.9% in 1998 to 3.7% in 2000, but then dropped to 0.8% in 2001 and to 1.4% in 2002. The unemployment rate responded with some delay. It decreased from 9.3% at the start of the observation period to 6.6% in 2001. In 2002 it increased again to 7.5%.[14] We therefore include in the specification of the transition rates the district unemployment rate, the regional growth rate of GDP, and seasonal indicators as quarterly time-varying explanatory variables. In the specification of the wage hazard rate, these variables are fixed at the quarter of job acceptance. Since standard statistics of the unemployment rate are not available at the local level, we rely on a non-standard definition, i.e. the ratio of UB recipients to the population insured against the risk of unemployment (thereby excluding civil servants). This explains why the reported unemployment rates are much higher than those based on the standard ILO definition. At the sampling date in 1998, the average district unemployment rate is respectively 18.7% for

[13]Because of collinearity with age and household type, the amount of UB cannot be included as a separate regressor. In 2000, the monthly benefit level ranged between 307€ for cohabitants older than 18 and 790€ for household heads.

[14]These figures are available in Internet at http://epp.eurostat.ec.europa.eu.

men and 27% for women, compared to 7.7% and 11.6% according to the ILO definition. The regional GDP growth rate is defined as the rate of change of the regional GDP from same quarter of the previous year. The average regional GDP growth at sampling date and at the start of the first employment spell is around 2% for both genders.

3 Econometric Modeling

To detect potential scarring effects of past unemployment experience on current labor market outcomes, we model the labor market histories as transitions between unemployment and employment in which the occurrence of and duration in previous labor market states affect transitions from the current state. The starting wage is modelled as an intermediate labor market state between unemployment and employment. Rather than imposing a log-normal wage distribution, we contribute to the literature by specifying a flexible form based on its characterization in terms of hazard rate. In Subsection 3.1 we introduce notation and specify the econometric model. In order to account for selection on unobservables, we allow for unobserved random effects that may be correlated between destination states of the modelled transitions. In subsection 3.2 we discuss how this unobserved heterogeneity can be identified and disentangled from (lagged) duration dependence. In subsection 3.3 the likelihood function is derived explicitly taking into account the time grouping of the labor market transitions in quarterly intervals and the left truncation of unemployment duration at the sampling date.

3.1 The Econometric Model

At the start of the observation period, unemployment, u, is the common origin state. There are two competing exit destinations from unemployment: employment, e, and an absorbing censoring state, a, which can be roughly categorized as out-of-labor force. We model it is as an absorbing state as to simplify the model and to focus on active workers. If employment is entered, a FTE monthly starting wage w is observed. Employment can also be left for two destinations: u and a. In a particular individual labor market history, one can observe a sequence of starting wages w and spells in u and e. For the sake of limiting the computational complexity, no more than two observations of this sequence are modelled. The order of realization within this sequence is denoted by superscript $s = 1, 2$.

Let $\mathbf{x}$ denote the vector of observed explanatory variables[15] and $\mathbf{V} \equiv (V_{ue}, V_{ua}, V_w, V_{eu}, V_{ea})$ be a random vector of transition specific fixed covariates that are unobserved to the analyst. These may capture factors such as unobserved productivity or household income.

[15] In the empirical analysis we allow for strictly exogenous (external) time-varying covariates. Introducing this time dependence would make the notation cumbersome. Since it is not a key feature we ignore it in the presentation of the econometric model.

T^s_{ok} denotes the latent duration in origin state o ending in destination state k. The observed duration is the minimum of the latent durations. W^s is the random accepted wage of the sth employment spell. Finally, $\mathbf{Y}^s \equiv [T^s_{ue}, T^s_{ua} > T^s_{ue}, W^s, T^s_{eu}, T^s_{ea} > T^s_{eu}]$ and $P(\mathbf{Z}|\mathbf{x}, \mathbf{V})$ denotes the (joint) conditional probability of a (vector of) random variable(s) $\mathbf{Z}$ conditional on $(\mathbf{x}, \mathbf{V})$.

We make the following assumptions, where $\mathbf{V}_{-i} \equiv (V_1, ..., V_{i-1}, V_{i+1}, ...V_I)$:

Assumption 1
$\forall s, o \in \{u, e\}, i \neq j : P(T^s_{oi}, T^s_{oj} > T^s_{oi}|\mathbf{x}, \mathbf{V}) = P(T^s_{oj}|\mathbf{x}, \mathbf{V})P(T^s_{oj} > T^s_{oi}|\mathbf{x}, \mathbf{V})$.

Assumption 2 $P(\mathbf{Y}^2|\mathbf{x}, \mathbf{V}, \mathbf{y}^1) = P(\mathbf{Y}^2|\mathbf{x}, \mathbf{V}, t^1_{eu})$.

Assumption 3 $\forall s, ok \in \{ue, ua, eu, ea\} : T^s_{ok} \perp\!\!\!\perp \mathbf{V}_{-ok}|(\mathbf{x}, V_{ok}), W^s \perp\!\!\!\perp \mathbf{V}_{-w}|(\mathbf{x}, V_w)$.

Assumption 1 states that the latent durations are independent conditional on the observed and unobserved covariates, i.e. that the competing risks are conditionally independent. By assumption 2, conditional on $(\mathbf{x}, \mathbf{V})$, the second vector of endogenous variables $\mathbf{Y}^2$ depends on $\mathbf{Y}^1$ only through the first realized employment duration t^1_{eu} and not through the first unemployment duration t^1_{ue} nor starting wage w^1. The dependence on t^1_{eu} captures the effect of general human capital accumulation or signaling on subsequent wages and labor market transitions. The unemployment duration and the starting wage affect subsequent labor market outcomes only indirectly through their effect on the subsequent employment duration. Finally, Assumption 3 implies that V_{ok} (V_w) captures the unobserved determinants of T^s_{ok} (W^s).

With these assumptions the joint conditional probability density function evaluated at the realization of $\mathbf{Y} \equiv (\mathbf{Y}^1, \mathbf{Y}^2)$, $\mathbf{y}$, is

$$
\begin{aligned}
P(\mathbf{y}|\mathbf{x}, \mathbf{V}) = \prod_{s=1}^{2} P\left(t^s_{ue}|\mathbf{x}, V_{ue}, \left[t^1_{eu}\right]^{\delta_{2s}}\right) P\left(T^s_{ua} > t^s_{ue}|\mathbf{x}, V_{ue}, \left[t^1_{eu}\right]^{\delta_{2s}}\right)& \\
\times P\left(w^s|\mathbf{x}, V_w, t^s_{ue}, \left[t^1_{eu}\right]^{\delta_{2s}}\right)& \\
\times P\left(t^s_{eu}|\mathbf{x}, V_{eu}, t^s_{ue}, w^s, \left[t^1_{eu}\right]^{\delta_{2s}}\right) P\left(T^s_{ea} > t^s_{eu}|\mathbf{x}, V_{eu}, t^s_{ue}, w^s, \left[t^1_{eu}\right]^{\delta_{2s}}\right)& \qquad (1)
\end{aligned}
$$

where δ_{2s} denotes the Kronecker delta, which is equal to one if $s = 2$ and zero otherwise. This represents the joint conditional probability if one observes two complete unemployment and employment spells. It is not difficult to see how this probability should be modified if an observation is incomplete either as a consequence of exogenous right censoring or because the absorbing state a is entered.

If the conditional marginal distributions on the right-hand side of (1) are absolutely continuous,[16] then they can be completely characterized by the corresponding hazard

[16] In the data the durations are measured in quarters. However, as explained in Section 3.3, we characterize their distribution as if they are generated by an underlying continuous time process.

rates. We assume that the hazard rates have a Mixed Proportional Hazard (MPH) specification and that the unobserved factors are independently distributed from the observed ones:

Assumption 4 *For $j \in \{e, a\}$ and $k \in \{u, a\}$:*

$$\theta_{uj}^{s}\left(t|\mathbf{x}, V_{ue}, \left[t_{eu}^{1}\right]^{\delta_{2s}}\right) = h_{uj}(t)\phi_{uj}(\mathbf{x})\varpi_{uj}(t_{eu}^{1})^{\delta_{2s}}V_{uj} \tag{2}$$

$$\theta_{w}^{s}\left(w|\mathbf{x}, V_{w}, t_{ue}^{s}, \left[t_{eu}^{1}\right]^{\delta_{2s}}\right) = h_{w}(w)\phi_{w}(\mathbf{x})\pi_{w}(t_{ue}^{s})\varpi_{w}(t_{eu}^{1})^{\delta_{2s}}V_{w} \tag{3}$$

$$\theta_{eu}^{s}\left(t|\mathbf{x}, V_{eu}, t_{ue}^{s}, w^{s}, \left[t_{eu}^{1}\right]^{\delta_{2s}}\right) = h_{ek}(t)\phi_{ek}(\mathbf{x})\pi_{ek}(t_{ue}^{s})\rho_{ek}(w^{s})\varpi_{ek}(t_{eu}^{1})^{\delta_{2s}}V_{ek} \tag{4}$$

Assumption 5 $\mathbf{V} \perp\!\!\!\perp \mathbf{x}$

The different components of the hazards have the following interpretation:

- The $h_{jk}(\cdot)$'s and $h_{w}(\cdot)$ are the baseline hazard functions, non-negative and common to all the individuals. Note that they do not depend on s. The order s of an outcome of interest is assumed to affect the hazard proportionally. This will become apparent in the specification of ϖ_r (for $r \in \{ue, ua, w, eu, ea\}$) below.
- The $\phi_{jk}(\mathbf{x})$'s and $\phi_{w}(\mathbf{x})$ are the non-negative systematic parts and functions of covariates. Note that by Assumption 5 we can only give this part a structural (behavioural) interpretation if there are no other unobserved factors which are correlated with $\mathbf{x}$. Otherwise, the observed variables just serve as control variables which purge for these correlated unobserved factors (Wooldridge, 2005).
- $\pi_{w}(t_{ue}^{s})$ and $\pi_{ek}(t_{ue}^{s})$ are the lagged unemployment duration dependence, i.e. the non-negative impact of unemployment duration t_{ue}^{s} on the wage hazard rate and the employment transition intensities, respectively.
- The $\varpi_{jk}(t_{eu}^{1})$'s and $\varpi_{w}(t_{eu}^{1})$ are non-negative and capture the occurrence dependence of the corresponding hazard function: $s = 2$ instead of $s = 1$. It is assumed that this shifts the hazards proportionally. In addition, this shift is allowed to depend on the duration of the first employment spell.
- $\rho_{ek}(w^{s})$ is non-negative and captures the impact of the starting wage w^{s} on subsequent employment transition intensities.
- The V_{jk}'s are non-negative random variables reflecting the unobserved individual determinants of the hazards.

Misspecification of the baseline hazard functions and too strict parametric assumptions are possible sources of bias. 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 $r = 1, \cdots, q$, $w_0 < w_1 < \cdots < w_q$, $w_0 \equiv \underline{w}$ is equal to the minimum observed wage, and $w_q = \infty$. We fix w_1 to the 5% percentile and w_{q-1} to the 95% percentile of the wage distribution. 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.[17] In this way segment widths are as narrow as 40€ and we obtain a very flexible specification of the monthly wage distribution.

The systematic parts are specified in a standard way:

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

We take the logarithm of the lagged dependent variables, so that the corresponding coefficients identify their proportional effect on the hazard rates:

$$\begin{aligned}
\varpi_r(t^1_{eu}) &= \exp\left[\alpha_r + \ln(t^1_{eu})\psi_r + UB_h \mathbb{1}_{\{ue,ua\}}(r)\omega_r\right] \text{ for } r \in \{ue, ua, w, eu, ea\}, \\
\pi_j(t^s_{ue}) &= \exp\left[\ln(t^s_{ue})\eta_j\right] \text{ for } j \in \{w, eu, ea\} \text{ and } s = 1, 2, \\
\rho_k(w^s) &= \exp\left[\ln(w^s)\gamma_k\right] \text{ for } k \in \{eu, ea\} \text{ and } s = 1, 2.
\end{aligned}$$

where $\mathbb{1}_{\{ue,ua\}}(r)$ denotes the indicator function, UB_h is an indicator variable equal to one if the level of UB is high, and $\exp(\alpha_r)$ is the proportional shift of the hazards if $s = 2$ rather than $s = 1$, referred to as *occurrence* dependence in the interpretation of the empirical results below. As mentioned in Section 2, UB_h is one if $t^1_{eu} > 4$ and it can therefore be treated as a particular parametrization of the lagged employment duration dependence.

While the hazard from (un)employment have a straightforward interpretation – loosely, it is the rate at which (un)employment is left for a particular destination given that the spell did not end before – the wage hazard is more difficult to interpret. The wage hazard evaluated at w is the probability density of earning a wage exactly equal to w, conditional on earning at least w. Individual characteristics and past labor market history affect this probability and thereby the corresponding wage distribution. A direct implication of modeling the wage distribution by means of a MPH specification is that a change in the covariates affect all the quantiles of the wage distribution in the same direction. To see this, consider the quantile function implied by the MPH specification of the hazard:

$$Q^s_w(q|\mathbf{x}, t^s_{ue}, V_w) = (H^s_w)^{-1}\left(\frac{-\ln(1-q)}{\exp\left[\mathbf{x}\beta_w + \ln(t^s_{ue})\eta_w + \delta_{2s}\left(\alpha_r + \ln(t^1_{ue})\psi_w\right)\right]v_w}\right), \quad (5)$$

where $(H^s_w)^{-1}(\cdot)$ is the inverse of the integrated wage baseline hazard $H^s_w(\cdot)$. It can be shown that, per each quantile $q \in [0, 1]$, the partial derivative of the quantile function (5) with respect to each variable has opposite sign to that of the corresponding parameter.

[17] This is somewhat arbitrary but derivation of an optimal rule for segment widths is beyond the scope of this study.

If, for example, $\eta_w < 0$, a marginal increase in the unemployment duration t^s_{ue} shifts the wage distribution in the sense of first order stochastic dominance. By contrast, if $\eta_w > 0$, the resulting distribution will be (first order) stochastically dominated.

In the special case that the wage baseline function is constant over the wage support, wages are exponentially distributed. In this case the MPH specification implies that observed and unobserved characteristics affect the log expected wages additively. This resembles the way in which covariates affect wages when these are log-normally distributed. However, as soon as one departs from a constant wage baseline hazard function, the additive relation between covariates and log expected wages is lost and the MPH structure shifts the log-integrated wage hazard function additively instead.

3.2 Identification

For the sake of clarity, the discussion on model identification starts from a simpler version of model (2)–(4). First, we assume that we observe only one sequence of realizations per individual of (un)employment transitions and wages, i.e. $s = 1$. Second, we assume that $\mathbf{x}$ does not contain time-varying variables.

Honoré (1993) showed that, under the MPH assumption, exogenous regressor variation, and auxiliary assumptions on either the first moment or on the tail behaviour of the mixing distribution, the model components, including lagged duration dependence, are non-parametrically identified in a single risk framework. Under similar assumptions, Horny and Picchio (2010) extend Honoré's (1993) proof to competing risks.

If multiple observations per individual are observed (Abbring and van den Berg, 2003a,b) and/or if exogenous information from time-varying variables is exploited (Brinch, 2007; Gaure et al., 2008), the aforementioned identification assumptions can be relaxed. The time-variation of exogenous variables is used to identify the causal impacts of endogenous variables also in dynamic discrete time panel data models (Bhargava, 1991; Mroz and Savage, 2006). The restrictions across time periods on the parameters of time-varying variables generate exclusion restrictions, as every lag of the exogenous time-varying variable could have a separate impact on the current realization of an outcome variable. Our model, in its most general specification, encompasses multiple realizations per individual of the outcome variables and we condition on strictly exogenous time-varying covariates. We therefore argue that, on the basis of the existing literature, our model is over-identified and the MPH assumption is not crucial for separating structural components and unobserved heterogeneity.

The aforementioned identification results are derived in a continuous time framework. By contrast, in our data the information on duration is grouped on a quarterly basis. As shown in Ridder (1990), non-parametric identification with discrete duration data requires more structure on the systematic parts of the unemployment and employment transition intensities, like a parametric structure $\phi_l(\mathbf{x}) = \exp(\mathbf{x}\beta_l)$ which takes on every value in $\Re_+$. However, Gaure et al. (2007) report from an extensive Monte Carlo analysis that, in practice, despite the time grouping of duration the true structural parameters can still be robustly recovered from the observed data, to the extent that the discreteness of data measurement is explicitly taken into account when setting up the likelihood function.

3.3 Likelihood Function

We only observe the labor market state occupied at the end of each quarter. The observed duration data are therefore measured in discrete time. As mentioned in Subsection 3.2, we explicitly take this discreteness into account. To avoid that the parameters depend on the time unit of observation (Flinn and Heckman, 1982), we follow van den Berg and van der Klaauw (2001) and specify the discrete-time process as if it was generated by a grouped continuous-time model.

The likelihood contribution for individual i with a complete unemployment duration spell s ending in $k \in \{e, a\}$ after t quarters and condtional on the unobserved heterogeneity is given by[18]

$$L_{iu}^{s}(t|\mathbf{x}, V_{ue}, V_{ua}; \mathbf{\Theta}_u) = \frac{\theta_{uk}^{s}(t-1|\mathbf{x}, V_{ue}, V_{ua})}{\sum_{k\in\{e,a\}}\theta_{uk}^{s}(t-1|\mathbf{x}, V_{ue}, V_{ua})} \times \left[S_u(t-1|\mathbf{x}, V_{ue}, V_{ua}) - S_u(t|\mathbf{x}, V_{ue}, V_{ua})\right], \tag{6}$$

where

- $S_u(t|\mathbf{x}, V_{ue}, V_{ua}) \equiv \prod_{\tau=1}^{t} \exp[-\sum_{k\in\{e,a\}}\theta_{uk}^{s}(\tau-1|\mathbf{x}, V_{ue}, V_{ua})]$, $\tau \in \mathbb{N}$, is the survivor function in unemployment.[19]
- $\mathbf{\Theta}_u$ is the set of unknown parameters in this likelihood contribution.

The conditional likelihood contribution of an incomplete unemployment spell is the survivor function in unemployment at the end of the observation period. The conditional likelihood contribution of employment spells has the same structure.

The conditional likelihood contribution of the sth starting wage w is equal to the wage density. If $w \in [w_{r-1}, w_r)$ and the baseline hazard of wages is piecewise constant, this density can be written in terms of the hazard as follows:

$$L_{iw}^{s}(w|\mathbf{x}, t_{ue}^{s}, V_w; \mathbf{\Theta}_w) = \theta_w^s(w|\mathbf{x}, t_{ue}^{s}, V_w)\exp\Big[-\sum_{j=1}^{r-1}\theta_w^s(w_{j-1}|\mathbf{x}, t_{ue}^{s}, V_w)(w_j - w_{j-1}) - \theta_w^s(w|\mathbf{x}, t_{ue}^{s}, V_w)(w - w_{r-1})\Big]$$

[18]See Appendix A.1 for a more detailed derivation of this likelihood contribution.

[19]Note that the survivor function is the likelihood contribution for a spell that is exogenously right censored at the end of the observation period (December 2002).

Individual i's conditional likelihood contribution is the product of all the individual i's single spell contributions. Denote this by $L_i^m \equiv L_i(\mathbf{V}; \mathbf{\Theta})$, where $\mathbf{\Theta} \equiv (\mathbf{\Theta}_u, \mathbf{\Theta}_w, \mathbf{\Theta}_e)$ is the set of parameters to be estimated. Since this likelihood contribution is conditional on the unobserved factors $\mathbf{V}$, we need to integrate them out.

Given that the model is non-parametrically identified, we follow Heckman and Singer (1984) by assuming that the heterogeneity distribution can be estimated by a discrete distribution function with a finite and, *a priori*, unknown number M points of support.[20] The probabilities associated to the points of support sum to one and, $\forall\ m = 1, \ldots, M$, are denoted by

$$p^m = \Pr(V_{ue} = v_{ue}^m, V_{ua} = v_{ua}^m, V_w = v_w^m, V_{eu} = v_{eu}^m, V_{ea} = v_{ea}^m) \equiv \Pr(\mathbf{V} = \mathbf{v}^m)$$

and specified as logistic transforms:

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

The individual likelihood contribution for individual i is then $L_i \equiv \sum_{m=1}^{M} p^m L_i^m$.

As all sampled individuals have been unemployed for nine months since graduation, a left truncation problem arises. We take this into account by following the conditional likelihood approach proposed by Ridder (1984). If the probability of becoming unemployed after graduation is proportional in observed and unobserved explanatory variables, the individual contribution to the likelihood function just needs to be divided by the probability of surviving three quarters in unemployment averaged over the unobserved heterogeneity distribution:

$$L_i^0 = \frac{\sum_{m=1}^{M} p^m L_i^m}{\sum_{m=1}^{M} p^m S_u(3|\mathbf{x}, V_{ue}, V_{ua})}. \tag{7}$$

We exploit information from multiple realizations per individual of unemployment durations and transitions to identify the survivor function in the denominator of (7). Gaure et al. (2007) show that this approach works quite well in removing from the parameter estimates the bias generated by the left truncation.

4 Estimation Results and Interpretation

The central question of this research is whether, for a population of long-term unemployed school-leavers, remaining unemployed rather than employed inflicts a scar on the future labor market career. To answer this question we first focus our discussion on the

[20]On the basis of Monte Carlo simulations Gaure et al. (2007) find that for datasets of size similar to the one used here the number points of support is best chosen by minimizing the Akaike Information Criterion (AIC). We follow this recommendation.

effect of elapsed unemployment duration on the transition rate from unemployment to employment and on the impact of lagged unemployment duration on the transition rate from employment back to unemployment. As an indirect cost of remaining unemployed might be the employment experience that is forgone, a second point of discussion is the extent to which the occurrence and duration of employment affect the subsequent starting wage and the subsequent labor market transitions in and out of employment. Finally, if lagged (un)employment experience affects the starting wage and the starting wage in turn affects the duration of employment, the indirect effect through the starting wage should also be taken into account. In order to get a quantification of these effects, we report in Section 5 the results of simulation exercises.

The quality of employment may decrease with unemployment duration for three main reasons. First, the longer one remains unemployed, the more general and specific human capital may be lost either directly through depreciation or indirectly by foregoing on-the-job training (Pissarides, 1992; Mroz and Savage, 2006). Second, potential employers may interpret a longer spell of inactivity as a negative signal of unobserved productivity (Vishwanath, 1989; Lockwood, 1991). However, if the true productivity is revealed during the employment relationship (Jovanovic, 1979), the negative impact on quality might not be long-lasting. Third, the negative duration dependence in the transition from unemployment to employment may rather reflect discouragement or the gradual drying up of informal search channels (Calvo-Armengol and Jackson, 2004; van den Berg and van der Klaauw, 2006). The latter may have long lasting detrimental effects to the extent that finding a job through informal referrals may positively affect the job match quality (Simon and Warner, 1992; Ioannides and Loury, 2004).[21]

In the literature (e.g. Arulampalam, 2001) it is argued that longer spells of unemployment do not necessarily penalize subsequent labor market careers. Unemployment may be productive in enabling the individual to find a job which better matches his/her skills and preferences. This argument holds if one contrasts individuals with a different entitlement duration to UB. Job search theory indeed predicts that a longer entitlement to UB increases the reservation wage and therefore job quality (Ehrenberg and Oaxaca, 1976; Card et al., 2007). However, a long-term unemployed worker is more likely to be liquidity constrained than a short-term unemployed worker, since savings and UB decline or expire. This lowers the reservation wage and, consequently, the quality of the subsequent employment.

In this study we contrast youth who, conditional on their household type, are all entitled, without any time limit, to the same constant flat rate UB.[22] Differential liquidity constraints are therefore not a source of variation of unemployment duration and cannot

[21] More recently, Loury (2006) and Bentolila et al. (2010) have questioned this positive effect.

[22] If the first employment spell lasts more than one year, the level of UB is higher than in the first unemployment spell. However, we explicitly control for this by including an indicator variable equal to one if benefits are high and zero otherwise.

explain the effects of unemployment duration on the labor market outcomes.[23]

The results reported for men are based on a model that allows for selective entry in the absorbing state, while for women exits to the censoring state are assumed to be independent from unobservables, since a log-likelihood ratio test cannot reject the null hypothesis of equality of the unobserved location points (v_{ua}^m and v_{ea}^m) in the transition rate to the absorbing censoring state (p-value equal to 0.572).[24] The discrete unobserved heterogeneity distribution has 3 probability mass points for both men and women.

In the main text we focus our discussion on the main variables of interest: the lagged endogenous variables. The complete estimation results can be found in Appendix A.2. These findings are in line with expectations and are therefore not further discussed.

4.1 The Direct Impact of Unemployment Duration

The top panel of Figure 1 display the baseline transition intensities from unemployment to employment as a function of elapsed duration. Table 3 reports the impacts of lagged unemployment duration on the starting wage and on the transition from employment to unemployment. For both genders, the baseline transition intensity to employment is clearly decreasing with elapsed unemployment duration, but the wage is not significantly affected by lagged unemployment duration. Lagged unemployment duration decreases the transition from employment to unemployment, but only significantly for men.

How can this evidence be matched to the theory? A decreasing transition rate with elapsed duration is compatible with both human capital depreciation (Pissarides, 1992) and negative signaling (Vishwanath, 1989; Lockwood, 1991). However, lagged unemployment duration does not significantly affect wages and the effect on employment duration is positive. These findings are not consistent with human capital depreciation: human capital depreciation implies a decrease of productivity with unemployment duration and, hence, a lower wage and a higher separation rate from employment. For similar reasons they are neither consistent with the drying up of informal search channels.

In contrast, the estimation results can be in agreement with signaling theory. At recruitment, a worker is hired at a wage and terms that are in accordance with the productivity signal, among which the elapsed unemployment duration, available to the employer at that moment. During the initial employment phase the employer learns about the true productivity of the worker (Jovanovic, 1979). If at a certain point the employer realizes that the true productivity is lower than expected on the basis of the signal at recruitment, among which unemployment duration, she will fire the worker. In contrast, if the true productivity is higher than expected, the employer has incentives to retain the worker, since

[23] Since the level of UB for most school-leavers is low, the liquidity constraint may still bind after a certain unemployment duration if their or their parents' savings (the analysis concerns youth) run out. In that case, we would however expect that such school-leavers accept employment of lower quality, of which we find no evidence.

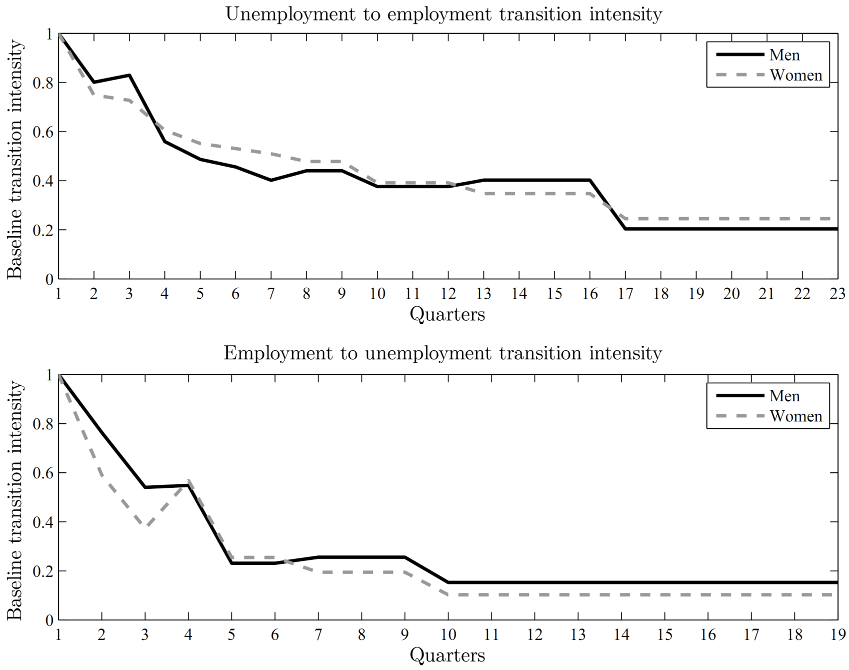
[24] For men this equality is confidently rejected (p-value equal to 0.0002).

Table 3: Estimation Results of the Lagged Dependence

Transition	ue			ua			w			eu			ea		
Variable	Coeff.		S.E.	Coeff.		S.E.	Coeff.		S.E.	Coeff.		S.E.	Coeff.		S.E.
Men															
Occurrence dependence (α_r)	-.033		.106	-.116		.109	-.089		.071	-.218	*	.130	.043		.161
$\ln$(lag employment duration) (ψ_r)	.013		.068	.087		.100	-.107	**	.051	-.027		.075	-.164		.107
$\ln$(lag unemployment duration) (η_j)	–		–	–		–	-.050		.039	-.187	***	.064	-.001		.093
$\ln$(starting wage) (γ_k)	–		–	–		–	–		–	-.142		.112	-.368	**	.144
Women															
Occurrence dependence (α_r)	.294	***	.097	.177	*	.089	-.136	*	.071	.069		.105	-.013		.143
$\ln$(lag employment duration) (ψ_r)	-.071		.048	.104		.064	-.128	***	.045	-.177	***	.060	-.172	*	.099
$\ln$(lag unemployment duration) (η_j)	–		–	–		–	-.062		.040	-.080		.059	.000		.074
$\ln$(starting wage) (γ_k)	–		–	–		–	–		–	-.226	**	.108	-.062		.142

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

Figure 1: Baseline Transitions Intensities to Employment and Unemployment



she has been hired under favourable terms from the employer perspective. This implies that a worker who had a shorter (longer) unemployment duration than expected on the basis of her true productivity will be fired (retained). Consequently, if we take out that part of the variation in unemployment duration at recruitment that is related to true productivity of a worker, which we do by conditioning on both observed and unobserved factors, the remaining variation in unemployment duration should be, as we observe, negatively related to the probability of dismissal.

If unemployment duration also partly reflects human capital depreciation, this negative relation with the probability of dismissal could disappear, since unemployment duration would then also reflect a genuine lower productivity. Such a depreciation is more likely to be the dominating factor for individuals with a certain work experience. On the one hand, for a recruiter past labor market experience may be a more reliable signal of productivity than unemployment experience.[25] On the other hand, unemployed experienced workers can incur in the depreciation of job-related human capital in addition to the depreciation of the learning skills acquired at school. This could explain why Böheim and Taylor (2002) find a positive relation between lagged unemployment duration and tenure for a representative sample of the working age population in the UK. In a model with a similar structure as in this paper, but which assumes that wages, unemployment durations, and

[25] McCormick (1990) suggests that firms use type of job held as an indicator of future productivity.

employment durations are log-normally distributed, Bratberg and Nilsen (2000) find, in line with our study, that unemployment duration significantly increases the duration of subsequent employment for school-leavers in Norway.

This positive relation between unemployment and employment duration may be breached in the presence of employment protection. Firing costs could make it too costly to dismiss a worker whose productivity is lower than expected at recruitment. Again this is less of an issue for school-leaving youth, since they are often hired in temporary jobs. Moreover, in Belgium employment protection in open-ended contracts is very weak during the first 6 months. For white collar workers there is a trial period of up to 6 months during which the employer can end the contract without any cost if notified 7 days in advance. For blue collar workers the trial period lasts only 7 days, but employment protection for these workers is much weaker than for confirmed white collar workers.

Finally, if unemployment duration is a signal of productivity, why does not it negatively affect the starting wage? We argue that this is a consequence of both the presence of (sectoral) minimum wages in Belgium and the low level of benefits to which the youth in our sample is entitled. From Table 2 one can deduce that 78% of the sample is cohabitant for whom the UB level is merely €307 (in 2000), while the national minimum wage for an 18 year old was €802. It is therefore most likely that the vast majority of these youngsters set their reservation wage at so low a level that they will not reject any job offer irrespective of their unemployment duration. Other studies focusing on youth find similar results (Ackum, 1991; Bratberg and Nilsen, 2000).

4.2 The Indirect Impact via Forgone Work Experience

By remaining unemployed a worker might forgo the long-term benefits of work experience, both in terms of occurrence and duration. First, consistent with the standard hypothesis of accumulation of general human capital through on-the-job training (Ben-Porath, 1967; Blinder and Weiss, 1976; Mroz and Savage, 2006), we find that employment experience significantly increases the starting wage of both genders at roughly the same rate.[26] On the basis of simulations we find that: i) increasing the lagged employment duration by 10% significantly increases the starting wage by 0.20% for men and 0.21% for women; ii) a one year increase in the lagged employment duration significantly increases the starting wage by 2.3% for men and 2.5% for women.

Standard human capital theory predicts that past employment experience may not only increase the wage, but also the duration of subsequent employment spells. We indeed find for women that increasing the duration of the previous employment spell by 10% decreases the likelihood of being dismissed by 1.6%.[27] We do not observe any significant

[26] Recall that a negative impact on the wage hazard corresponds to a positive impact on the average wage and on all quantiles of the wage distribution.

[27] $(1 - \exp(-.177))/10 = .016$.

effect for men, but this may be related to a multicollinearity problem: even if neither the occurrence nor the duration of past employment has separately any significant effect on the dismissal rate, they are jointly significant (p-value equal to 0.029).

Another standard finding (Topel and Ward, 1992; Farber, 1999) is that the dismissal probability decreases sharply with elapsed employment duration (see the bottom panel of Figure 1). The spike after 4 quarters observed for women might reflect the non-renewal of temporary contracts.

Finally, past employment experience, irrespective of its duration, affects the job finding rate for women but not for men. For women, the job finding rate after the employment experience (i.e. during the second unemployment spell) is 34.2%[28] higher that the job finding rate during the first unemployment spell. Apparently, it is more important for women than for men to signal that they are really interested in working rather than taking up responsibilities in the household.

To our knowledge only Doiron and Gørgens (2008) have studied the impact of past employment experience on labor market transitions of youth. In contrast to our study, these authors did not find any evidence for dependence of labor market transitions on past employment experience.

4.3 The Impact of the Starting Wage on the Transition from Employment

There is some consensus in theoretical models that higher wages induce longer lasting job relationships. According to on-the-job search models (see e.g., Burdett, 1978; Mortensen, 1986), employee's probability of voluntarily quitting the ongoing job decreases with the wage, since optimal job search effort and the probability of finding a higher-paid job decline with the actual wage. Furthermore, if the wage is considered as an incentive device (Shapiro and Stiglitz, 1984), high-wage employees have stronger incentives in exerting higher effort and lower chances of being detected shirking than those of comparable low-wage workers.[29] High-wage workers' probability of being laid off (their job tenure and hence employment duration) is thereby expected to be lower (longer) than that of comparable low-wage workers.

On the other hand, in the framework *à la* Jovanovic (1979), where the productivity of a particular worker-firm match is not observable *ex-ante* but is revealed *ex-post*, if the true productivity is revealed to be lower than expected, the starting wage is too high relative to the true productivity. To the extent that the wage is downward rigid, e.g. because youth is hired at the sectoral minimum wage, the probability of dismissal increases. Therefore, conditional on their true productivity, as captured by the observed and unobserved indi-

[28] $\exp(0.294) - 1 = 0.342$.

[29] The positive relationship between the wage and effort has been assessed by Cappelli and Chauvin (1991), Drago and Heywood (1992), and Fehr and Falk (1999).

vidual characteristics, high-wage workers face a higher probability of being laid off than comparable low-wage workers.

Consistent with the findings of Bratberg and Nilsen (2000) for Norwegian school-leavers, our findings indicate that the first mentioned theoretical prediction dominates. A 10% increase in the wage reduces the transition rate from employment to unemployment by 1.4% and from employment to out of the labor force by 3.7% for men. However, only the latter is significantly different from zero at the 5% level. For women these effects are 2.3% and 0.6%, of which only the first one is significant at the 5% level. The finding that the wage affects transition from employment to unemployment less for men than for women suggests that Jovanovic's (1979) explanation is more important for men than for women. This is in line with the finding reported in Subsection 4.1 that lagged unemployment duration decreases the likelihood of dismissal only significantly for men.

Finally, observe that the net positive effect of the wage on employment duration imposes an additional indirect scarring effect of unemployment duration on the labor market career, since the foregone labor market experience negatively affects the starting wage which in turn shortens the subsequent employment spell.

5 Simulations

From the estimation results reported in the previous section, we cannot conclude that staying unemployed unambiguously inflicts a scar on long-term unemployed school-leavers. In this section we therefore present the results of simulations that aim at identifying which of the opposing effects dominate and at deducing policy conclusions from this research. To this end, we first assess by simulations the goodness-of-fit of the estimated model.

5.1 Goodness-of-Fit

To construct goodness-of-fit statistics of the model, we simulate 999 labor market histories for each individual in the sample. By drawing each time from the assumed Normal distribution of parameter estimates, we construct 95% confidence intervals of the empirical distributions of unemployment and employment duration, and of starting wages that reflect both the parameter uncertainty and the uncertainty inherent in the outcome variable of interest. The goodness-of-fit can easily be checked by verifying whether the observed frequencies lie within these confidence intervals. In Appendix A.3 we list the steps involved in the simulation procedure.

Table 4 contrasts the actual unemployment duration, starting wage, and employment duration frequencies with the simulated counterparts and reports simulated confidence intervals. The model fits the wage and employment duration very well, but there is a tendency to overpredict the frequency of short unemployment spells while long unemployment spells are somewhat underpredicted.

Table 4: Goodness-of-Fit

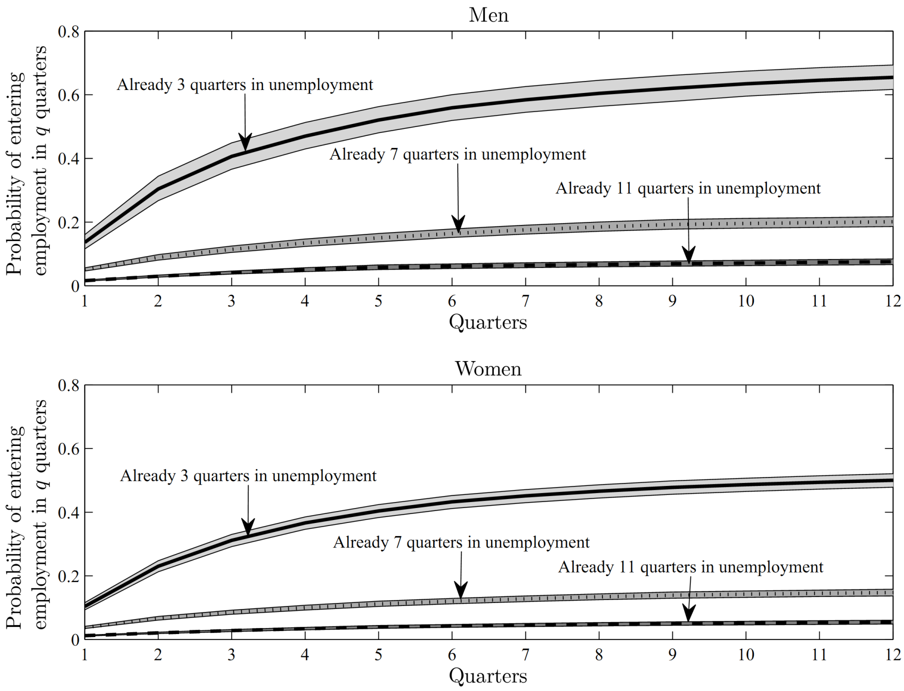
	Men				Women			
	Actual frequencies	Simulated frequencies	95% confidence interval		Actual frequencies	Simulated frequencies	95% confidence interval	
Quarters			Unemployment duration distribution					
1	.080	.100	.087	.114	.080	.102	.091	.112
2	**.040**	.042	.036	.049	**.040**	.041	.035	.046
3	**.029**	.027	.022	.033	**.027**	.026	.022	.031
4	.127	.161	.143	.180	.116	.141	.129	.153
5	.178	.198	.182	.214	.169	.192	.179	.205
6	**.119**	.116	.105	.129	**.115**	.111	.101	.121
7	**.079**	.082	.072	.092	**.082**	.084	.075	.093
8-9	**.119**	.114	.103	.126	**.117**	.118	.108	.128
10-12	.099	.087	.076	.097	**.101**	.092	.084	.101
13-16	.065	.054	.046	.061	**.066**	.059	.053	.066
17-23	.064	.019	.016	.024	.089	.034	.029	.039
Percentiles (€)			Wage distribution					
5	**950**	918	917	950	**883**	851	850	883
10	**1,017**	988	983	1,017	**917**	917	917	917
15	**1,050**	1,045	1,017	1,050	**983**	957	950	983
20	**1,083**	1,080	1,050	1,083	**1,017**	993	983	1,017
25	**1,117**	1,108	1,083	1,117	**1,050**	1,021	1,017	1,050
30	**1,150**	1,119	1,117	1,150	**1,050**	1,050	1,050	1,050
35	**1,150**	1,150	1,150	1,150	**1,083**	1,083	1,050	1,083
40	**1,183**	1,181	1,150	1,183	**1,117**	1,114	1,083	1,117
45	**1,217**	1,208	1,183	1,217	**1,150**	1,134	1,117	1,150
50	**1,250**	1,231	1,217	1,250	**1,183**	1,155	1,150	1,183
55	**1,250**	1,256	1,250	1,283	**1,183**	1,184	1,183	1,217
60	**1,283**	1,291	1,283	1,317	**1,217**	1,217	1,183	1,250
65	**1,317**	1,329	1,317	1,350	**1,250**	1,251	1,217	1,283
70	**1,383**	1,373	1,350	1,383	**1,283**	1,289	1,250	1,317
75	**1,417**	1,412	1,383	1,417	**1,317**	1,336	1,317	1,350
80	**1,450**	1,450	1,417	1,483	**1,383**	1,382	1,350	1,417
85	**1,483**	1,502	1,483	1,550	**1,417**	1,452	1,417	1,483
90	**1,583**	1,606	1,583	1,650	**1,517**	1,564	1,517	1,617
95	**1,717**	1,749	1,717	1,783	**1,683**	1,719	1,683	1,783
Quarters			Employment duration distribution					
1	**.243**	.218	.196	.244	**.257**	.245	.227	.265
2	**.141**	.130	.116	.146	**.122**	.120	.107	.134
3	**.090**	.086	.075	.098	**.082**	.080	.070	.090
4	**.074**	.072	.062	.083	**.087**	.086	.075	.096
5-6	**.077**	.075	.064	.085	**.086**	.086	.076	.097
7-9	**.101**	.098	.087	.110	**.091**	.092	.082	.104
10-18	.274	.321	.280	.360	**.276**	.292	.270	.314

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

5.2 The Impact of Unemployment Duration on the Job Finding Probability

The top panel of Figure 1 clearly displays that for both genders the baseline transition intensity from unemployment to employment is decreasing with unemployment duration. The first simulation exercise is aimed at quantifying the impact of this negative duration dependence on the cumulative job finding probability. We contrast three different counterfactuals. In the first one, the benchmark, we select all sampled youths. These youths have an elapsed unemployment duration of three quarters at that moment. In the second and in the third scenarios, we forced these youths to remain unemployed for, respectively, one and two additional years, so that at the start of the simulation of their labor market history they have been unemployed during, respectively, 7 and 11 quarters. Under these 3 different scenarios, we simulate transition intensities from unemployment and we compute the cumulative job finding probability within q quarters, with $q = 1, \ldots, 12$, counting from the moment at which individuals are no longer in forced unemployment. In order to focus on the effect of elapsed unemployment duration, we fix in this and subsequent simulations the time-varying variables to their time-average over the observation period.

Figure 2: Probability of Finding a Job in q Quarters by Gender



Notes: The grey areas are Monte Carlo 95% confidence intervals, computed by 999 replications.

Figure 2 displays the evolution of the cumulative job finding probability in the three scenarios. It demonstrates that the negative duration dependence in the hazard to employment remains very important despite that in the benchmark simulation the selected youth have already been unemployed for 3 quarters. For example, the probability of finding a job within two years decreases from 60% (47%) in the benchmark to 16% (13%) if the sampled men (women) had been unemployed for 7 quarters at the sampling date. If youths are forced to be unemployed for 11 quarters at the sampling date, the job finding probability within two years drops further to 7% for men and 5% for women.

5.3 The Impact of Unemployment Duration on Employment Stability

In Section 4.1 (Table 3) we reported that a prolonged unemployment spell may be compensated by a lower separation rate in the subsequent employment spell. Here we evaluate whether this compensation can eliminate the negative impact of unemployment duration on the job finding rate by quantifying the impact of lagged unemployment duration on the survivor rate in employment.

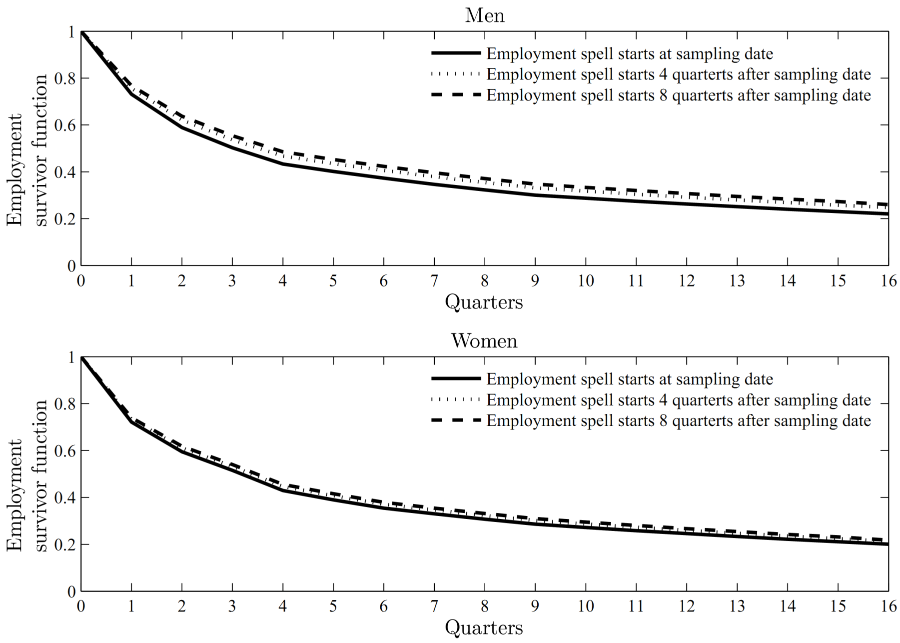
We contrast again three different counterfactuals. In the first one, youths are forced into employment at the sampling date, i.e. after 3 quarters in unemployment. In the second and in the third scenarios, they are all assigned a job after a forced sojourn of 4 and 8 more quarters into unemployment, respectively. Under these 3 different scenarios, we simulate starting wages and employment durations and we compute the corresponding survivor probabilities in employment.

Figure 3 displays these survivor probabilities. For men, the probability of surviving in employment for two years is 32% if a job is entered at the sampling date, while it significantly increases to 36% (37%) if the lagged unemployment duration is 4 (8) quarters longer.[30] For women, the probability of surviving in employment for two years increases not significantly from 31% to 32% (33%) if a job is entered 4 (8) quarters after the sampling date rather than at the sampling date. Even if for men a longer unemployment duration has a significant and positive impact on the employment survivor probability, the size of the effect is small, especially compared to the size of the effects reported in the previous subsection.

We therefore conclude that even for long-term unemployed youth it remains urgent to find employment as quickly as possible, since otherwise they risk to get stuck in unemployment. This conclusion is reinforced if we take into account the indirect effect of unemployment experience via foregone work experience on employment duration and on the wage in particular, as discussed in Subsection 4.2.

[30] The impact on the employment survivor function due to an increase in unemployment duration of 4 and 8 quarters is different from zero at the 1% significance level all along the survivor function.

Figure 3: Probability of Surviving in Employment by Gender



6 Conclusions

This research focused on Belgian long-term youth who remained more than nine months in unemployment after leaving school. In Belgium, school-leavers who are still unemployed nine months after graduation are entitled, without any time limit, to flat rate UB. We studied whether further unemployment experience beyond this inactivity period is harmful in terms of subsequent labor market outcomes.

We found that the job finding probability exhibits important negative duration dependence even after controlling for fixed observed and unobserved characteristics. For example, if the job-market entry is further delayed by one year, the probability of finding a job in the following two years decreases from 60% to 16% for men and from 47% to 13% for women. The unemployment duration does not, however, impose a direct scar in terms of employment quality: starting wages are not affected by the lagged unemployment duration and the employment stability increases (significantly only for men) with the lagged unemployment duration. Simulations revealed that the latter effect is quite small relative to negative duration dependence in the job finding rate. The duration of the previous unemployment spell does, nevertheless, impose an indirect scar through forgone work experience as we find evidence of past employment experience increasing future starting wages (by about 2.5% for each year of experience) and decreasing the future dismissal rate, especially for women.

We inferred from these findings that the cost of prolonged unemployment is not so much related to depreciation of human capital while unemployed, but rather to foregoing the human capital accumulation on-the-job and in particular to the negative signal that prolonged unemployment conveys to potential recruiters. We argued that the (mild) positive impact of unemployment duration on the length of the subsequent employment spell cannot be explained by more selective job acceptance behaviour, but rather by the fact that the signal conveyed by unemployment duration at recruitment may be reversed at the moment that the true productivity of the worker is revealed (Jovanovic, 1979). This explanation holds only, however, if true productivity remains roughly constant over the period of analysis (as it does here), so that it is captured in the econometric model by the fixed observed and unobserved individual characteristics.

These findings lead to the conclusion that curative intervention remains urgent even if youths are already long-term unemployed. Since human capital depreciation is not so much an issue for youths, the supply of training does not seem the right response. Our analysis suggests that offering employment experience as quickly as possible is more effective. We do not however study which concrete form this policy should take (recruitment subsidies, job referral, compulsory or not, etc.).

The flexible analysis of wages within a multivariate dynamic duration model proposed in this study was successful in fitting the wage distribution very closely and avoiding thereby biases induced by strict parametric assumptions on the wage distribution. We believe that this approach therefore merits to be explored further. Arni et al. (2009) have already successfully applied this approach to evaluate the impact of active labor market policies.

Appendix

A.1 Deriving the Likelihood Function

The contribution to the likelihood function of an unemployment spell that ends after t quarters in employment is the probability that the latent duration T_{ue} ends after τ quarters times the probability that the latent durations T_{ua} is longer than τ quarters.[31] In the data duration is measured in discrete time. If we assume that this discrete time process is generated by some underlying continuous time process in which at most one transition per quarter can occur and if we assume that this transition occurs at some arbitrary moment within the t-th quarter ($\tau \in [t-1, t)$), then the likelihood contribution of an unemployment

[31]The conditioning on observed and unobserved factors is implicit here. We also ignore the superscript s for notational convenience.

spell that ends in employment within the t-th quarter is given by:

$$\begin{aligned} L_{iu}(t) &= \int_{t-1}^{t} P(T_{ue}=\tau)P(T_{ue}>\tau)d\tau \\ &= \int_{t-1}^{t} \theta_{ue}(\tau)\exp\Big\{-\int_{0}^{\tau}\sum_{k\in\{e,a\}}\theta_{uk}(s)ds\Big\}d\tau. \end{aligned} \tag{A.1}$$

If the baseline hazards of the latent durations are assumed to be piecewise constant within each quarter, then the integral can be solved and the integrated hazard rewritten as a sum of piecewise constant hazards evaluated at the start of each interval:

$$L_{iu}(t) = \frac{\theta_{ue}(t-1)}{\sum_{r\in\{e,a\}}\theta_{ur}(t-1)}\big[S_u(t-1)-S_u(t)\big], \tag{A.2}$$

where

$$S_u(t) = \exp\Big\{-\sum_{j=1}^{t}\sum_{k\in\{e,a\}}\theta_{uk}(j-1)\Big\} \tag{A.3}$$

is the survivor function in unemployment. Reintroducing the set of observed and unobserved characteristics yields the likelihood contribution (6) in the main text. The contribution to the likelihood function of an unemployment spell that ends in the absorbing censoring state, a, is given by replacing θ_{ue} with θ_{ua} in the numerator of equations (A.2) and (6). The contribution of employment spells are derived in the same way. The likelihood contribution of a spell that is right censored at the end of the observation period in December 2002 is given by the corresponding survivor function at that point.

A.2 Further Estimation Results

Table A.1: Estimation Results of the Systematic Parts and Unobserved Heterogeneity Distribution – Men

Transition	ue			ua			w			eu			ea		
Variable	Coeff.		S.E.	Coeff.		S.E.	Coeff.		S.E.	Coeff.		S.E.	Coeff.		S.E.
Time-invariant covariates															
Age/10	-.291		.181	-.477	***	.147	-.029		.107	-.209		.178	-.259		.221
Nationality – Reference: Belgian															
Non-Belgian EU	.086		.113	-.124		.101	-.186	***	.066	.132		.109	-.022		.148
Non EU	-.041		.119	-.190	*	.114	-.115	*	.069	.142		.119	.076		.137
Education – Reference: Higher secondary															
Primary or none	-.957	***	.115	-.172	*	.104	.217	***	.069	.901	***	.138	.522	***	.195
Lower secondary	-.715	***	.088	-.146	**	.074	.161	***	.050	.622	***	.102	.288	**	.146
Post secondary	.543	***	.106	.232	***	.077	-.664	***	.060	-.404	***	.109	-.104		.149
Region of residence – Reference: Wallonia															
Flanders	.621	***	.121	.226	**	.101	-.095		.076	-.161		.134	.268		.171
Brussels	.100		.089	.111		.076	.206	***	.048	-.040		.085	.154		.106
Quarter of sample entry – Reference: April-May-June															
Jan-Feb-Mar	.048		.104	.083		.084	-.003		.062	-.031		.101	.179		.112
Jul-Aug-Sep	-.336	***	.082	.321	***	.067	.088	*	.050	.286	***	.089	.147		.114
Oct-Nov-Dec	-.149		.095	.094		.087	.095	*	.057	.122		.099	.248	**	.112
Household position – Reference: Cohabitant															
Head of household	-.840	***	.106	-.169	*	.103	-.031		.075	.442	***	.120	.023		.175
Single	-.344	***	.082	.084		.072	.074		.049	.517	***	.092	.277	**	.119
Kids $[0, 3)$ years old	-.060		.153	-.073		.143	-.144		.094	.005		.148	.054		.178
High benefits	-.375	***	.124	2.458		1.992	–		–	–		–	–		–
Time-variant covariates															
Regional GDP growth	7.001	***	1.463	-1.917	***	.500	-.602		1.190	-.869		1.595	.219		2.256
District unem. rate	-1.925	***	.516	-.008		.059	-.409		.383	1.660	***	.629	-.758		.786
Quarterly indicators – Reference: April-May-June															
Jan-Feb-Mar	-.028		.043	.129	**	.058	-.023		.037	.294	***	.065	.242	***	.093
Jul-Aug-Sep	-.043		.046	.060		.061	.005		.035	.238	***	.065	.179	*	.092
Oct-Nov-Dec	-.163	***	.049	-.029		.187	-.066	*	.037	.186	***	.068	.192	**	.093
Individual heterogeneity distribution – $M = 3$															
Support points															
$\ln v_{jk}^1$	-.490	***	.180	-1.747	***	.190	-7.120	***	.144	-1.896	***	.207	-3.058	***	.286
$\ln v_{jk}^2$	-1.867	***	.225	-2.174	***	.257	-6.914	***	.190	-1.031	***	.317	-2.768	***	.459
$\ln v_{jk}^3$	.542	***	.195	$-\infty$		–	-7.379	***	.156	-2.760	***	.275	-2.834	***	.348
Probability masses (logistic transform)							*Resulting probabilities*								
λ_1	.348	**	.144				p_1	.558							
λ_2	-2.116	***	.288				p_2	.047							
λ_3	.000		–				p_3	.394							
No. of individuals								6,277							
No. of parameters								179							
Log-likelihood								-47,873.6							

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

Table A.2: Estimation Results of the Systematic Parts and Unobserved Heterogeneity Distribution – Women

Transition	ue			ua			w			eu			ea		
Variable	Coeff.		S.E.	Coeff.		S.E.	Coeff.		S.E.	Coeff.		S.E.	Coeff.		S.E.
Time-invariant covariates															
Age/10	.048		.123	-.320	***	.098	-.589	***	.110	-.184		.145	.146		.202
Nationality – Reference: Belgian															
Non-Belgian EU	-.003		.078	-.169	**	.070	.152	**	.070	.008		.091	.008		.134
Non EU	-.814	***	.085	-.235	***	.062	.135		.089	.202	*	.103	-.176		.165
Education – Reference: Higher secondary															
Primary or none	-.900	***	.085	-.177	***	.057	.199	**	.090	.573	***	.103	.581	***	.139
Lower secondary	-.705	***	.056	.002		.039	.280	***	.053	.422	***	.069	.177	*	.093
Post secondary	.913	***	.083	.396	***	.051	-.972	***	.061	-.273	***	.095	-.073		.089
Region of residence – Reference: Wallonia															
Flanders	.591	***	.074	.219	***	.060	.012		.062	-.062		.088	.320	***	.108
Brussels	.155	**	.069	.047		.052	.002		.059	-.199	**	.078	.150		.105
Quarter of sample entry – Reference: April-May-June															
Jan-Feb-Mar	-.084		.078	.059		.059	-.104		.065	-.014		.091	.117		.117
Jul-Aug-Sep	-.207	***	.058	.263	***	.041	-.113	**	.050	.017		.067	.174	*	.091
Oct-Nov-Dec	-.300	***	.079	.160	***	.056	-.025		.077	.180	**	.087	.275	**	.129
Household position – Reference: Cohabitant															
Head of household	-.856	***	.072	-.150	***	.047	.039		.071	.148		.093	.167		.124
Single	-.088		.066	.074		.050	-.097	*	.053	.058		.069	.216	**	.095
Kids $[0, 3)$ years old	-.576	***	.072	.024		.049	.010		.073	.119		.093	.169		.128
High benefits	-.146		.109	-.176		.151	–		–	–		–	–		–
Time-variant covariates															
Regional GDP growth	6.752	***	1.355	-1.853		1.606	1.186		1.211	-1.436		1.395	.257		2.193
District unem. rate	-1.477	***	.309	-1.431	***	.265	.868	***	.274	.741	**	.354	-.255		.514
Quarterly indicators – Reference: April-May-June															
Jan-Feb-Mar	.007		.043	-.248	***	.047	-.011		.037	.328	***	.061	.173	**	.086
Jul-Aug-Sep	.076	*	.046	.114	***	.044	-.012		.036	.406	***	.061	.212	**	.085
Oct-Nov-Dec	-.039		.047	-.073		.048	-.052		.036	.068		.065	-.046		.090
Individual heterogeneity distribution – $M = 3$															
Support points															
$\ln v^1_{jk}$	-.637	***	.156	-2.118	***	.157	-7.150	***	.150	-1.903	***	.177	-3.153	***	.262
$\ln v^2_{jk}$	-1.753	***	.181	–		–	-7.081	***	.169	-1.403	***	.250	–		–
$\ln v^3_{jk}$	-.342	*	.185	–		–	-8.398	***	.186	-1.731	***	.226	–		–
Probability masses (logistic transform)							*Resulting probabilities*								
λ_1	1.980	***	.264				p_1	.634							
λ_2	1.158	***	.289				p_2	.279							
λ_3	.000		–				p_3	.088							
No. of individuals								8,433							
No. of parameters								176							
Log-likelihood								-58,798.7							

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

Table A.3: Estimation Results of Unemployment and Employment Baseline Hazard Functions by Gender

Transition	ue			ua				eu			ea		
Quarters	Coeff.		S.E.	Coeff.		S.E.	Quarters	Coeff.		S.E.	Coeff.		S.E.
							Men						
2nd	-.290	***	.076	-.171		.151	2nd	-.269	***	.063	-.219	**	.102
3rd	-.318	***	.093	-.043		.167	3rd	-.616	***	.082	-.240	**	.111
4th	-.502	***	.098	-.153		.136	4th	-.601	***	.090	-.277	**	.119
5th	-.596	***	.104	.163		.138	5th-6th	-1.466	***	.106	-.618	***	.115
6th	-.633	***	.113	.090		.144	7th-9th	-1.363	***	.102	-.743	***	.116
7th	-.674	***	.117	-.019		.148	10th-18th	-1.878	***	.118	-1.074	***	.128
8th-9th	-.737	***	.116	-.233		.146							
10th-12th	-.938	***	.127	-.266		.159							
13th-16th	-1.057	***	.137	-.172		.169							
17th-23rd	-1.405	***	.155	-.587	***	.193							
							Women						
2nd	-.259	***	.075	.111		.124	2nd	-.527	***	.058	-.331	***	.105
3rd	-.246	***	.094	.438	***	.128	3rd	-.987	***	.073	-.148		.105
4th	-.420	***	.099	.067		.116	4th	-.567	***	.069	-.236	**	.115
5th	-.478	***	.106	.369	***	.117	5th-6th	-1.368	***	.079	-.467	***	.106
6th	-.518	***	.116	.194		.123	7th-9th	-1.636	***	.084	-.753	***	.110
7th	-.555	***	.120	.240	**	.122	10th-18th	-2.276	***	.101	-.697	***	.104
8th-9th	-.589	***	.120	.181		.119							
10th-12th	-.750	***	.133	.182		.124							
13th-16th	-.874	***	.145	.087		.125							
17th-23rd	-1.220	***	.164	.084		.130							

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

Table A.4: Estimation Results of the Wage Baseline Hazard Function by Gender

	Men			Women		
Wage support segments	Coeff.		S.E.	Coeff.		S.E.
Reference: $[w_0, w_1)$						
$[w_1, w_3)$	2.491	***	.104	2.637	***	.098
$[w_3, w_4)$	2.898	***	.115	3.058	***	.104
$[w_4, w_5)$	3.304	***	.113	3.424	***	.106
$[w_5, w_6)$	3.618	***	.113	3.692	***	.109
$[w_6, w_7)$	4.000	***	.101	3.978	***	.099
$[w_7, w_8)$	3.992	***	.099	3.975	***	.098
$[w_8, w_9)$	4.036	***	.100	4.278	***	.095
$[w_9, w_{10})$	4.288	***	.104	4.448	***	.101
$[w_{10}, w_{11})$	4.176	***	.121	4.528	***	.111
$[w_{11}, w_{12})$	4.226	***	.117	4.588	***	.114
$[w_{12}, w_{13})$	4.248	***	.114	4.581	***	.112
$[w_{13}, w_{14})$	4.635	***	.108	4.813	***	.110
$[w_{14}, w_{15})$	4.767	***	.118	5.147	***	.117
$[w_{15}, w_{16})$	4.754	***	.139	4.852	***	.155
$[w_{16}, w_{17})$	4.251	***	.177	4.855	***	.157
$[w_{17}, w_{18})$	4.501	***	.150	4.939	***	.152
$[w_{18}, w_{19})$	4.448	***	.165	4.980	***	.161
$[w_{19}, w_{21})$	4.632	***	.133	5.227	***	.134
$[w_{21}, w_{22}]$	4.899	***	.112	5.527	***	.123

Note: *** Significant at 1% level.

A.3 Simulation Algorithms

Simulations with Regard to the Goodness-of-Fit

Left truncation complicates the simulation procedure. 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. The distribution of the unobserved heterogeneity conditional on surviving three quarters in unemployment after school departure can be derived from Bayes' theorem. The probability p_i^m that individual i is of type m and is therefore assigned the vector of location points $\hat{\mathbf{v}}^m \equiv [\hat{v}_{ue}^m, \hat{v}_{ua}^m, \hat{v}_w^m, \hat{v}_{eu}^m, \hat{v}_{ea}^m]$ for $m = 1, \ldots, \widehat{M}$ can be estimated by

$$\hat{p}_i^m = \frac{\widehat{S}_u(3|\mathbf{x}_i; \widehat{\Theta}_u, \hat{v}_{ue}^m, \hat{v}_{ua}^m)\hat{p}^m}{\sum_{r=1}^{\widehat{M}} \widehat{S}_u(3|\mathbf{x}_i; \widehat{\Theta}_u, \hat{v}_{ue}^r, \hat{v}_{ua}^r)\hat{p}^r}, \tag{A.4}$$

where $\widehat{M} = 3$ for men and women. Observe that this distribution depends on the values of the observed explanatory variables at the sampling date and it is not therefore independent of the other covariates.

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 using the estimated variance-covariance matrix.[32]
2. Assign to each individual the observed explanatory variables at the sampling date and a vector of unobserved characteristics drawn with the probability as given in Equation (A.4).
3. Simulate the transition from u to e or a by a sequence of quarterly transition lotteries starting from the 4^{th} quarter (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 $\frac{L_{iu}(t)}{S_{iu}(t-1)}$. In this process, the time-varying variables (the local unemployment rate, the regional GDP variation, and the quarterly dummies) are adjusted to their new values at the beginning of each quarter.
4. If a transition to the absorbing state a occurs, the simulation for that individual is halted. If there is a transition to e, assign values to the local unemployment rate, the regional GDP variation, and the quarterly dummies according to the quarter of entry into the sample and to the unemployment duration. On the basis of the empirical distribution of wages corresponding to the theoretical wage hazard function in Equation (3), simulate the wage on the basis of individual lotteries.

[32]This allows us to take the parameter uncertainty into account and to build Monte Carlo confidence intervals.

5. Simulate the transitions from e according to a similar sequence of quarterly lotteries as described for unemployment in point 3. The time-varying explanatory variables are adjusted taking into account the quarter of entry in the sample and the duration of the unemployment spell.
6. If a transition from e to the censoring state a occurs, the simulation for that individual is halted. In case of a transition from e to u, simulate the duration of the second unemployment spell and the destination state as in point 3 but starting from the 1^{st} quarter. The subsequent starting wage and employment spell are simulated as in points 4 and 5.
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 $R = 999$ times to obtain R independent labor market histories for each sampled individual.

Simulations with Regard to the Evaluation Exercises

The simulation to quantify the impact of unemployment duration dependence on the probability of finding a job proceeds as follows:

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 observed explanatory variables at the sampling date and a vector of unobserved characteristics drawn with the probability as given in Equation (A.4).[33]
3. Compute for each individual the unconditional probability of moving from unemployment to employment as in Equation (A.2), $\forall t = 1, \ldots, 23$.
4. To obtain the average probability of finding a job in q quarters ($\forall q = 1, \ldots, 12$) if youths start looking for a job as soon as they are sampled, compute the cumulative sum from $t = 4$ to $q + 3$ of the unconditional probability at point 3 and average across the sample. If youths start looking for a job 4 (8) quarters after the sampling date the cumulative sum is calculated from $t = 8$ to $q + 7$ ($t = 12$ to $q + 11$).
5. Repeat points 1 to 4 $R = 999$ times to obtain R independent realizations and compute Monte Carlo confidence intervals.

The simulation to quantify the impact of lagged unemployment duration on employment stability proceeds first as in point 1 and 2 of the preceding simulation. Subsequently,

[33] In order to isolate the effect of the unemployment duration dependence from the effect induced by changes in the time-varying covariates, the time-varying covariates are fixed at their time average over the observation period.

3. Simulate for each sampled individual the first starting wage and the duration of the first employment spell as described in the simulation algorithm with regard to the goodness-of-fit and by fixing the lagged unemployment duration to 3 quarters, 7 quarters, and 11 quarters.
4. For each of the three counterfactuals, compute the Kaplan-Meier estimates of the employment survivor function.
5. Repeat points 1 to 4 $R = 999$ times to obtain R independent realizations and compute Monte Carlo confidence intervals.

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