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

Bart Cockx† and Matteo Picchio‡

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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 labour market outcomes. We propose a flexible method for analysing the effect on wages aside of transitions from unemployment and employment within a multivariate duration model which 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 signalling and not by human capital depreciation.

Keywords: duration dependence, employment quality, scarring effect of unemployment duration, selectivity, wage in multivariate duration model.

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†Sherppa, Ghent University, Tweekerkenstraat 2, B-9000 Gent, Belgium; UCLouvain (IRES), Louvain-la-Neuve; IZA, Bonn; CESIfo, Munich. E-mail: bart.cockx@ugent.be.

‡Sherppa, Ghent University, Tweekerkenstraat 2, B-9000 Gent, Belgium; Research Foundation - Flanders (FWO), Belgium; CentER, Department of Economics, Tilburg University, The Netherlands; IZA, Bonn. E-mail: matteo.picchio@ugent.be.

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. 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 as ten years ago 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. (Ellwood, 1982; Kletzer and Fairlie, 2003) and in Europe (Arulampalam, 2001; Gregg, 2001; Gregg and Tominey, 2005; Gartell, 2009). 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 in unemployment after leaving school. More insight into this issue provides valuable information for the design of curative policy for long-term unemployed youth.

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 labour 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.

An advantage of this modelling approach is that it identifies the sources of the scarring effect of unemployment duration. Unemployment duration can affect labour 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 labour market dynamics, such as human capital or signalling, are relevant in explaining the labour market transitions of disadvantaged youth at the start of their labour 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 labour market state of interest. This leads to the so-called "sample selectivity problem" (Heckman, 1979). We explicitly control for selectivity 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 (Belzil, 1995, 2001; Jurajda, 2002; Tatsiramos, 2009) or to analyse the effect of lagged state and duration dependence on labour market transitions (Böheim and Taylor, 2002; Doiron and Gørgens, 2008; Cockx and Picchio, 2011a). A few researchers have integrated the effect on wages within this framework, but assumed that wages are log-normally distributed conditional on covariates (Bratberg and Nilsen, 2000; Gaure et al., 2008; McCall and Chi, 2008). This research contributes to the literature by proposing a flexible estimator of the wage distribution and by modelling 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. By doing so, we also extend the model used by Cockx and Picchio (2011a) to analyse labour market transitions in a correlated competing risks framework by incorporating also wages. Arni et al. (2012) have used our framework to estimate the impact of benefit sanctions on earnings.

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 of delaying the first employment experience. Section 6 concludes.

2 The Data

The empirical analysis is conducted on administrative records gathered by the Crossroads Bank for Social Security (CBSS). The CBSS merges data from the different Belgian Social Insurance institutions and allows thereby to construct the quarterly labour market history of all Belgian workers. The data include real gross quarterly earnings, deflated by the consumer price index of January 2001, 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. 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.

The sample retains all Belgian youth, aged between 18 and 25 years, who, shortly after graduating from education, registered as job seeker at the Public Employment Service and who did not find any job during the following nine months. 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 labour 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 labour 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 labour force, enters a training program or self-employment, returns to school, or is sanctioned and loses the UB eligibility. We model the exit to these states as absorbing to reduce computational complexity.

These states define four potential transitions: ue, ua, eu, and ea. The starting wage (w) is modelled as an intermediate labour 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. Figure 1 illustrates this first sequence ($s = 1$) of the modelled labour market states and transitions. The first unemployment spell can be left either for employment with a particular starting wage or for the absorbing endogenous censoring state. The first employment spell can in turn be left either for unemployment or for the censoring state. At the start of this second unemployment spell the second sequence of states is modelled in the same way as the first. To limit computational complexity, we restrict the empirical analysis to maximum two of the aforementioned sequences of labour market states per individual. Not much information is lost, however, since these two sequences cover around 92% of the total number of unemployment and employment spells in the data.

Figure 1: The First Sequence ($s = 1$) of Modelled Labour Market States and Transitions

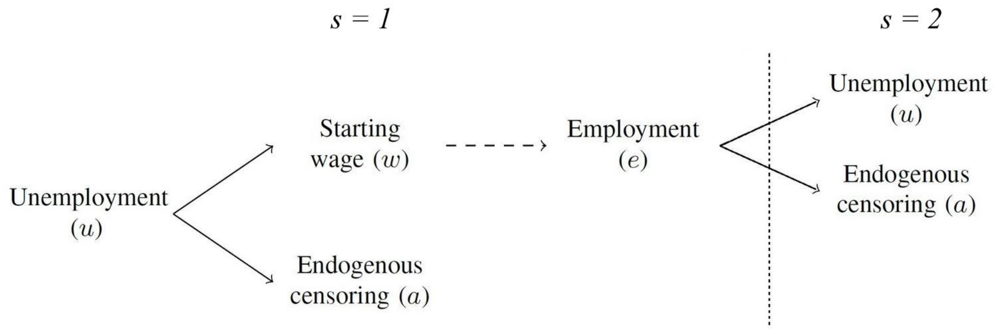


Table 1 reports, by gender, descriptive statistics on the endogenous variables: unemployment and employment durations, transitions from the origin states, the FTE monthly wage at the beginning of the corresponding employment spell and the fraction of spells in which the unemployed are entitled to a higher UB. The last mentioned variable is endogenous, since this entitlement 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

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[a]	1	2	1
50th	7[a]	2	4	4
75th	10[a]	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[a]	1	2	2
50th	7[a]	2	4	4
75th	11[a]	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 uninterruptedly employed for more than one year.

the second unemployment spell, respectively seven and two quarters, both for men and for women. This is a consequence of the sample selection rule requiring school-leavers to be unemployed nine months before showing up for the first time in the administrative records of the CBSS. The median duration of the first and second 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. Finally, the national minimum needs not to be satisfied at each instant, but only on average within a year.

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

Age, presence in the household of kids younger than three 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 those living in Wallonia and Brussels.

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.

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. Cohabitants live in a household in which at least one other member earns an income exceeding this threshold. Singles live 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. 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. 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 labour 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% (Eurostat). We therefore include in the specification of the transition rates the district unemployment rate, the regional GDP growth rate, and seasonal indicators as quarterly time-varying explanatory variables. In the specification of the wage hazard rate, these variables are fixed in 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. The regional GDP growth rate is defined as the rate of change of the regional GDP from the same quarter of the previous year.

3 Econometric Modelling

To detect potential scarring effects of past unemployment experience on current labour market outcomes, we allow for lagged occurrence of and duration dependence in the transition rates between labour market states. The starting wage is modelled as an intermediate labour 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. We correct for selectivity by allowing unobserved random effects to be correlated between destination states. 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 labour 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-labour 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 starting wage w is observed. Employment can also be left for two destinations: u and a. An individual labour market history is thus characterized by a set of labour market sequences consisting in an unemployment spell, a wage, and an employment spell, possibly interrupted by an exit to the absorbing state. As already mentioned in Section 2, we only model two such sequences. The order of this sequence is denoted by superscript $s = 1, 2$.

Let $\mathbf{x}$ denote the vector of observed explanatory variables. 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. Denote by $\mathbf{V} \equiv (V_{ue}, V_{ua}, V_w, V_{eu}, V_{ea})$ a random vector of non-negative transition specific fixed covariates that are unobserved to the analyst. Under certain conditions that we state below Assumption 5, these may be correlated with $\mathbf{x}$ and thus capture unobserved factors like productivity, parental income, or parental education. T^s_{ok} denotes the random latent duration in origin state o ($o \in \{u, e\}$) ending in destination state k ($k \in \{u, e, a\} \wedge k \neq o$) within the sth labour market sequence ($s \in \{1, 2\}$). The observed duration t^s_{ok} is the realized minimum of the latent durations. W^s is the random accepted wage of the sth employment spell. Finally, $\mathbf{Y}^s \equiv [\min\{T^s_{ue}, T^s_{ua}\}, W^s, \min\{T^s_{eu}, T^s_{ea}\}]$ denotes the sth random labour market sequence.

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

Assumption 1
$\forall s \in \{1, 2\}, \forall o, i, j \in \{u, e\}, i \neq j: \quad P(T^s_{oi}, T^s_{oj}|\mathbf{x}, \mathbf{V}) = P(T^s_{oj}|\mathbf{x}, \mathbf{V})P(T^s_{oj}|\mathbf{x}, \mathbf{V})$.

Assumption 2 $P\big(\mathbf{Y}^2|\mathbf{x}, \mathbf{V}, \mathbf{Y}^1 = [t^1_{ue}, w^1, t^1_{eu}]\big) = P\left(\mathbf{Y}^2|\mathbf{x}, \mathbf{V}, t^1_{eu}\right)$.

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

Assumption 1 states that the latent durations are independent conditional on the observed and unobserved covariates, i.e. 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 signalling on subsequent wages and labour market transitions. The unemployment duration and the starting wage affect subsequent labour 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, and denoting $\mathbf{Y} \equiv (\mathbf{Y}^1, \mathbf{Y}^2)$, $\mathbf{y} \equiv (\mathbf{y}^1, \mathbf{y}^2)$ and $\mathbf{y}^s \equiv$

$[t_{ue}^s, w^s, t_{eu}^s]$ $(s = 1, 2)$, the joint conditional probability density function of $\mathbf{Y} = \mathbf{y}$ is

$$P(\mathbf{Y} = \mathbf{y}|\mathbf{x}, \mathbf{V}) = \prod_{s=1}^{2} P\left(T_{ue}^s = t_{ue}^s|\mathbf{x}, V_{ue}, \left[t_{eu}^1\right]^{\delta_{2s}}\right) P\left(T_{ua}^s > t_{ue}^s|\mathbf{x}, V_{ue}, \left[t_{eu}^1\right]^{\delta_{2s}}\right)$$
$$\times P\left(W^s = w^s|\mathbf{x}, V_w, t_{ue}^s, \left[t_{eu}^1\right]^{\delta_{2s}}\right)$$
$$\times P\left(T_{eu}^s = t_{eu}^s|\mathbf{x}, V_{eu}, t_{ue}^s, w^s, \left[t_{eu}^1\right]^{\delta_{2s}}\right) P\left(T_{ea}^s > t_{eu}^s|\mathbf{x}, V_{eu}, t_{ue}^s, w^s, \left[t_{eu}^1\right]^{\delta_{2s}}\right) \tag{1}$$

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, then they can be completely characterized by the corresponding hazard rates. We assume that the hazard rates have a Mixed Proportional Hazard (MPH) specification:

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

$$\theta_{uj}^s\left(t|\mathbf{x}, V_{ue}, \left[t_{eu}^1\right]^{\delta_{2s}}\right) = h_{uj}(t)\phi_{uj}(\mathbf{x})\varpi_{uj}(t_{eu}^1)^{\delta_{2s}}V_{uj} \tag{2}$$
$$\theta_{w}^s\left(w|\mathbf{x}, V_{w}, t_{ue}^s, \left[t_{eu}^1\right]^{\delta_{2s}}\right) = h_{w}(w)\phi_{w}(\mathbf{x})\pi_w(t_{ue}^s)\varpi_{w}(t_{eu}^1)^{\delta_{2s}}V_{w} \tag{3}$$
$$\theta_{ek}^s\left(t|\mathbf{x}, V_{ek}, t_{ue}^s, w^s, \left[t_{eu}^1\right]^{\delta_{2s}}\right) = h_{ek}(t)\phi_{ek}(\mathbf{x})\pi_{ek}(t_{ue}^s)\rho_{ek}(w^s)\varpi_{ek}(t_{eu}^1)^{\delta_{2s}}V_{ek} \tag{4}$$

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. 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 functions of the observed covariates $\mathbf{x}$.

- $\pi_w(t^s_{ue})$ and $\pi_{ek}(t^s_{ue})$ capture the lagged unemployment duration dependence, i.e. the non-negative impact of past unemployment duration t^s_{ue} on the wage and employment hazard.
- The $\varpi_{jk}(t^1_{eu})$'s and $\varpi_w(t^1_{eu})$ are non-negative and capture the dependence of the second labour market sequence $\mathbf{Y}^2$ on the first $\mathbf{y}^1$. As stated in Assumption 2, this dependence is restricted to be a function of the first employment duration t^1_{eu} only.
- $\rho_{ek}(w^s)$ is non-negative and captures the impact of the starting wage w^s on subsequent employment 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. Regarding the wage hazard rate, the wage support is divided in q intervals $I_l = [w_{l-1}, w_l)$, where $l = 1, \cdots, q$, $w_0 < w_1 < \cdots < w_q$, $w_0 \equiv \underline{w}$ is equal to the minimum observed wage, and $w_q = \infty$. We fix w_1 to the 5th percentile and w_{q-1} to the 95th percentile of the wage distribution. We choose the width of the wage baseline segments by dividing the wage support between these percentiles of the unconditional wage distribution in 20 equally spaced intervals. 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:

$$\phi_r(\mathbf{x}) = \exp(\mathbf{x}\beta_r), \quad \text{for } r \in \{ue, ua, w, eu, ea\}.$$

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.

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

In the literature it is usually assumed that the unobserved covariates $\mathbf{V}$ are independent of the observed covariates $\mathbf{x}$. However, if we impose a functional form restriction on the relationship between the unobservables and the observables, then dependence can be allowed for (Cockx et al., 2010). To see this, denote the dependent unobserved covariates by V_{xr} ($r \in \{ue, ua, w, eu, ea\}$) and assume that $V_{xr} = \exp(\mathbf{x}\mu_r)V_r$. It is obvious that, with this specification of the dependence, β_r cannot be separately identified from μ_r. This means that the coefficients of $\mathbf{x}$ just serve as control variables that purge for these correlated unobserved factors and can therefore no longer be given a structural interpretation. However, the other parameters are still identified, in particular those relative to the (lagged) endogenous variables, which are the ones of interest. This functional form assumption is strong, but the approach is just an application of the widely used one in the analysis of nonlinear panel data originally proposed by Chamberlain (1980).

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 labour market history affect this hazard and thereby the corresponding wage distribution. A direct implication of modelling 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:

$$Q_w^s(q|\mathbf{x}, t_{ue}^s, V_w) = (H_w^s)^{-1}\left(\frac{-\ln(1-q)}{\exp\left[\mathbf{x}\beta_w + \ln(t_{ue}^s)\eta_w + \delta_{2s}\left(\alpha_w + \ln(t_{ue}^1)\psi_w\right)\right]v_w}\right), \quad (5)$$

where $(H_w^s)^{-1}(\cdot)$ is the inverse of the integrated wage baseline hazard $H_w^s(\cdot)$. It can be shown that, per each quantile $q \in [0, 1]$, the sign of the partial derivative of the quantile function (5) with respect to each variable is opposite to the sign of the corresponding parameter. If, for example, $\eta_w < 0$, the wage distribution that results from a marginal increase in the unemployment duration t_{ue}^s first order stochastically dominates the initial one. By contrast, if $\eta_w > 0$, the resulting distribution is (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 if 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 labour market sequence, 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; Horny and Picchio, 2009) and/or if exogenous information from time-varying variables is exploited (Brinch, 2007), the aforementioned identification assumptions can be relaxed. In dynamic discrete time panel data models (Bhargava, 1991; Mroz and Savage, 2006) the time-variation of exogenous variables is also used to identify the causal impacts of endogenous variables. 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 hazards, like a parametric structure $\phi_r(\mathbf{x}) = \exp(\mathbf{x}\beta_r)$ which takes on every value in $\Re_+$. However, Gaure et al. (2007) report from an extensive Monte Carlo analysis that, 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 labour market state occupied at the end of each quarter. The observed duration data are therefore measured in discrete time and 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 generated by a grouped continuous-time model.

The likelihood contribution for individual i with a complete unemployment spell s

ending in $k \in \{e, a\}$ after t quarters and conditional on the unobserved heterogeneity is given by

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

where

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

See Cockx and Picchio (2011a, Appendix A) for a more detailed derivation of the likelihood contribution in (6). 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:

$$L^s_{iw}(w|\mathbf{x}, t^s_{ue}, V_w; \mathbf{\Theta}_w) = \theta^s_w(w|\mathbf{x}, t^s_{ue}, V_w) \exp\Bigg[-\sum_{j=1}^{r-1} \theta^s_w(w_{j-1}|\mathbf{x}, t^s_{ue}, V_w)(w_j - w_{j-1}) - \theta^s_w(w|\mathbf{x}, t^s_{ue}, V_w)(w - w_{r-1})\Bigg].$$

Individual i's conditional likelihood contribution is the product of all the individual i's single spell contributions. Denote this by $L^m_i \equiv L_i(\mathbf{V}; \mathbf{\Theta})$, 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. 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. 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 $L_i \equiv \sum_{m=1}^{M} p^m L_i^m$.

Since 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:

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

In this procedure the baseline hazards of the first unemployment spell are assumed to be equal to those of the second spell, apart from a proportional shift, i.e. the occurrence dependence $\exp(\alpha_{uj})$ $(j = e, u)$. However, this assumption may be too strong, since in the first spell, in contrast to the second, the unemployed are not entitled to UB during the first three quarters. This may induce a different profile of the hazard in this initial period. We therefore performed a sensitivity analysis, available on request, in which we considered two extreme alternative assumptions. First, we assumed a constant baseline hazard during the first three quarters. Second, we imposed an extreme negative duration dependence by setting the hazard rate to zero in the second and the third quarter. We did not consider positive duration dependence, since this is implausible given that the unemployed can anticipate that they are entitled to UB as from the fourth quarter onwards. These two alternative models did not have any major impact on the parameters of interest, namely those that are related to the (lagged) duration dependence.

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 labour market career. Unemployment duration can affect the labour market career in at least three ways. First, it may directly affect the speed of transition to employment from the current unemployment spell and the quality of subsequent employment spell as measured by its duration and by the level of the starting wage. Second, the time spent in unemployment is employment experience that is forgone. Third, if lagged (un)employment experience affects the starting wage and the starting wage in turn affects the employment duration, the indirect effect through the starting wage should also be taken into account.

We focus our discussion on the estimation results that help clarifying this central question, i.e. on the parameter estimates of the lagged endogenous variables. The discussion is organized in three subsections according to the three aforementioned potential effects of unemployment duration on the labour market career. We relate these findings to the existing theoretical and empirical literature. However, since unemployment duration affects the labour market career in opposing directions, the estimation results do not allow us to conclude whether or not remaining unemployed is detrimental for the further development of the career. To answer this question, we perform some simulation exercises and report them in Section 5. Finally, we do not discuss the impact of other explanatory variables, since this is not the focus of this study. We just note that they are in line with expectations and report them in Appendix A.1.

The estimation results for men are based on a model that allows for selective entry in the absorbing state. For women exits to the censoring state are assumed to be independent of 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). For men this equality is confidently rejected (p-value equal to 0.0002). The discrete unobserved heterogeneity distribution has 3 probability mass points for both men and women.

4.1 The Direct Impact of Unemployment Duration

The top panel of Figure 2 displays 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 theory? A decreasing transition rate with elapsed duration is compatible with both human capital depreciation (Pissarides, 1992) and negative signalling (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.

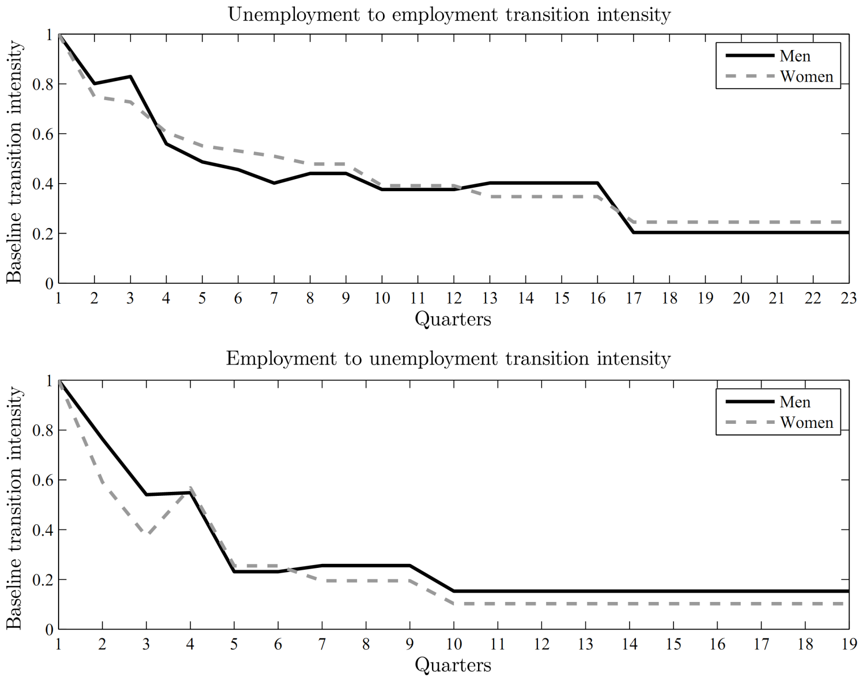
In contrast, the estimation results can be in agreement with signalling theory. At recruitment, a worker is hired at a wage and terms that are in accordance with the productivity signal, among which the elapsed unemployment duration, available to the employer at that moment. During the initial employment phase the employer learns about the true productivity of the worker (Jovanovic, 1979). If at a certain point the employer realizes

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 2: Baseline Transitions Intensities to Employment and Unemployment



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 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.

In a similar model, but with wages, unemployment durations, and employment durations log-normally distributed, Bratberg and Nilsen (2000) find, as in this study, that unemployment duration significantly increases the duration of subsequent employment for school-leavers in Norway, once controlled for unobserved heterogeneity. In line with the literature (e.g. Arulampalam, 2001), they argue, however, that this higher quality of the job match is explained by the fact that they have been searching longer rather than by the aforementioned arguments. Job search theory can indeed explain a positive association between unemployment duration and job match quality (Ehrenberg and Oaxaca, 1976; Card et al., 2007). Long-term unemployment and jobs of higher quality are positively associated *because* individuals are more selective, i.e. set a higher reservation wage. However, *for a given reservation wage*, this positive association disappears. We argue that we estimate the effect of unemployment duration on the subsequent starting wage and employment duration, *conditional on the reservation wage*, since we believe that the reservation wage is captured by the (time-varying) observables and the unobservables for which we control. To our opinion, job search theory cannot therefore explain our findings.

The sampled individuals on which we base our analysis are all entitled to a constant flat rate UB without any time limit. Individuals returning to unemployment after an intervening spell of employment of at least one year are entitled to a higher UB, but we control for this by means of a time-varying indicator. This means that the UB system does not induce time variation in the reservation wage that is not captured by the control variables in the econometric model. The included time-varying variables (regional growth rate of GDP, unemployment rate at the district level and seasonal indicators) capture the variation in the reservation wage (and job arrival rate) due to changing business cycle or seasonal conditions. If anything, the econometric model may fail in capturing the falling reservation wage in anticipation of the lower job arrival rate or in anticipation of potential increased liquidity constraints at longer unemployment duration. However, if so, we would expect a *lower* reservation wage, and hence a lower quality of subsequent employment for the long-term unemployed and not a *higher*, as we find.

In contrast to Bratberg and Nilsen (2000) and our results, Böheim and Taylor (2002) find that the duration of the previous unemployment spell has no significant effect on the exit rate into unemployment for a representative sample of the working age population in the UK. The fact that their sample is not restricted to school-leavers, but also contains experienced workers may explain this different finding. On the one hand, for a recruiter past labour market experience may be a more reliable signal of productivity than unemployment experience. McCormick (1990) suggests that firms use type of job held as an indicator of future productivity. On the other hand, unemployed experienced workers can incur depreciation of job-related human capital in addition to learning skills acquired at school. This may cancel out the aforementioned signalling effect for this group of workers and explain the insignificant effect.

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-leavers, 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 the one 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. 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%. We do not observe any significant 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 2). 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% 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 labour market transitions of youth. In contrast to our study, these authors did not find any evidence for dependence of labour 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.

In a framework *à la* Jovanovic (1979), where the productivity of a particular worker-firm match is not observable *ex-ante* but is revealed *ex-post*, the relationship between starting wage and employment duration may reverse. 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 individual 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, we find 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 labour 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 labour market career, since the foregone labour 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 labour 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. The steps involved in the simulation procedure are described in Appendix A.3 of Cockx and Picchio (2011b).

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

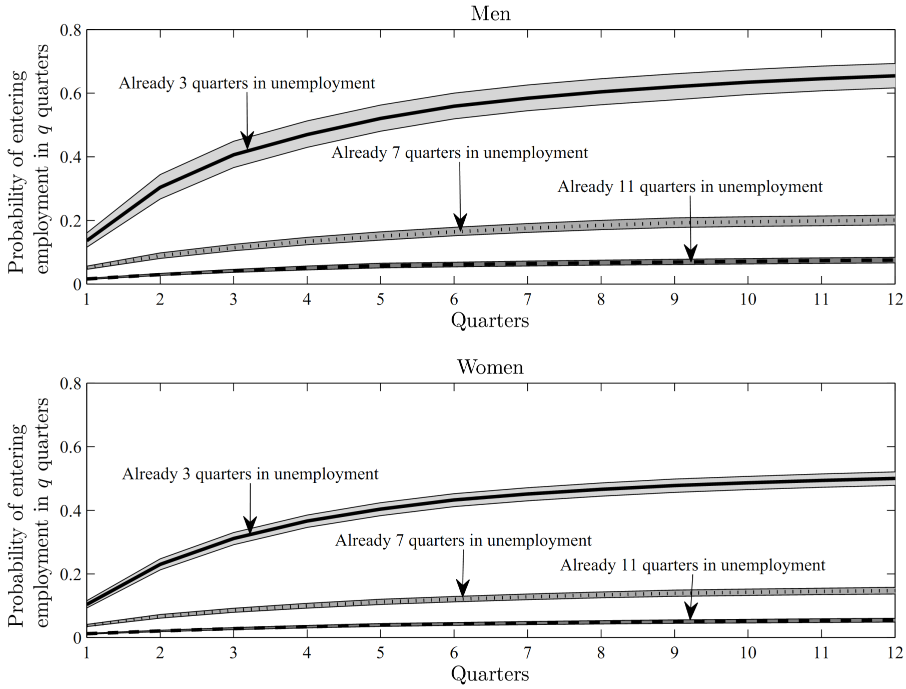
Note: Actual frequencies lying in the 95% confidence intervals of the simulated frequencies are in bold.

5.2 The Impact of Unemployment Duration on the Job Finding Probability

The top panel of Figure 2 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 labour 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 3 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.

Figure 3: Probability of Finding a Job in q Quarters by Gender



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

5.3 The Impact of Unemployment Duration on Employment Stability

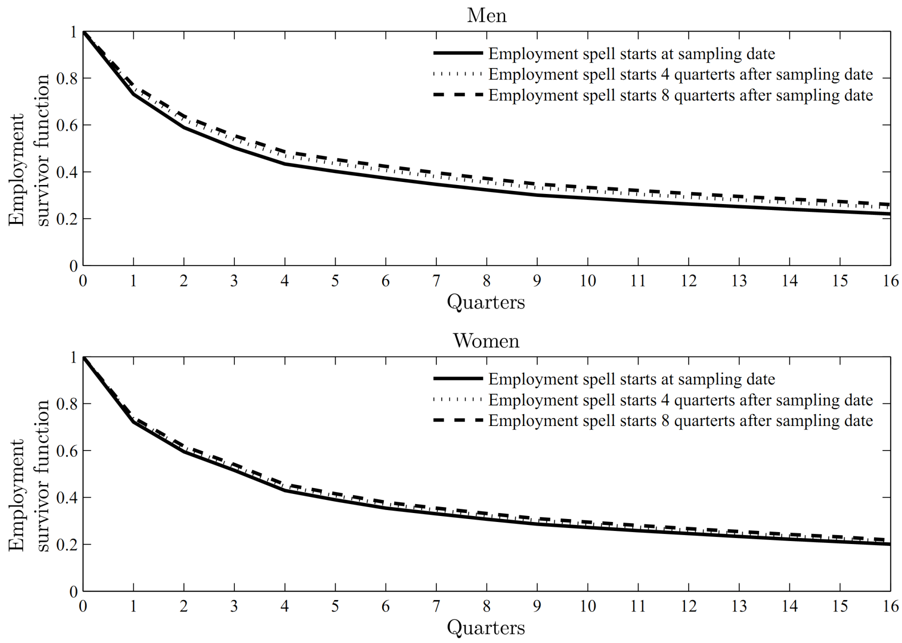
In Section 4.1 (Table 3) we reported that a prolonged unemployment spell may be compensated by a lower separation rate in the subsequent employment spell. Here we quantify the impact of lagged unemployment duration on the survivor rate in employment in order to understand whether it may compensate the negative impact of unemployment duration on the job finding rate.

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 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 4 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. 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.

Figure 4: Probability of Surviving in Employment by Gender



6 Conclusions

This research focused on Belgian 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 labour 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 the 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 work 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 to the negative signal that prolonged unemployment conveys to potential recruiters. We argued that the (mild) direct 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).

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 therefore believe that this approach merits to be explored further. Arni et al. (2012) have already successfully applied this approach to evaluate the impact of active labour market policies.

Appendix

A.1 Further Estimation Results

Table A.1: 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.2: 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.

Table A.3: 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															
$\ln v^1_{jk}$	-.490	***	.180	-1.747	***	.190	-7.120	***	.144	-1.896	***	.207	-3.058	***	.286
$\ln v^2_{jk}$	-1.867	***	.225	-2.174	***	.257	-6.914	***	.190	-1.031	***	.317	-2.768	***	.459
$\ln v^3_{jk}$	.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.4: 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															
$\ln v_{jk}^1$	-.637	***	.156	-2.118	***	.157	-7.150	***	.150	-1.903	***	.177	-3.153	***	.262
$\ln v_{jk}^2$	-1.753	***	.181	–		–	-7.081	***	.169	-1.403	***	.250	–		–
$\ln v_{jk}^3$	-.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.

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