Are Short-Term Jobs Springboards to Long-Term Jobs? A New Approach*

Bart Cockx[†] and Matteo Picchio[‡]

Abstract

This paper assesses whether short-term jobs (lasting one quarter or less) are springboards to long-term jobs (lasting one year or more) for long-term unemployed school-leavers in Belgium. We proceed in two steps. First, we estimate the complete labour market trajectory of these workers on the basis of a multi-state multi-spell duration model that incorporates the effects of past labour market outcomes on subsequent labour market transitions. Subsequently, we simulate the model to investigate whether workers who enter short-term jobs are more or less likely to find a long-term job than in the counterfactual in which short-term jobs are rejected. The study concludes that the probability of entering a long-term job is, within two years, enhanced by 19 (14) percentage points for (wo)men. Short-term jobs are indeed springboards to long-term jobs.

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JEL classification codes: C15, C41, J62, J64

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[†]IRES and Department of Economics, Université catholique de Louvain, Place Montesquieu, 3, B-1348 Louvain-la-Neuve, Belgium. IZA, Bonn and CESIfo, Munich. E-mail: `bart.cockx@uclouvain.be`.

[‡]IRES and Department of Economics, Université catholique de Louvain, Place Montesquieu, 3, B-1348 Louvain-la-Neuve, Belgium. E-mail: `matteo.picchio@uclouvain.be`.

1 Introduction

Youth unemployment is particularly high in Belgium. The European Union Labour Force Survey reported that the average unemployment rate in Belgium attained 8.4% in 2005. In contrast, the youth unemployment rate, for those aged between 15 and 24, was 21.5% and exactly equal to the rate in 1995. In the EU-15 area, the youth unemployment rate has instead decreased from 21.2% in 1995 to 16.8% in 2005. Policy makers are therefore in the search of strategies that could bring this unemployment rate down. However, active labour market strategies for youth have in general not been very successful (Kluve 2006). It is therefore important to identify policies that do work for youth. One option is to encourage young workers to acquire labour market experience as soon as possible and accept any job, even if it is short-term or paying a low wage. However, one can argue, as trade-unions often do, that this is not a promising strategy, since, by accepting precarious positions, the worker risks to end up in a secondary labour market in which she cycles between low quality jobs and unemployment. In this paper we investigate whether or not short-term jobs, lasting one quarter or less, are a springboard to long-term jobs, lasting one year or more. The analysis is performed on a group of particularly disadvantaged youth in Belgium: school-leavers without any job experience during the nine months period since they graduated. On the basis of administrative data we were able to reconstruct the quarterly labour market history of these individuals over a four year period, from 1998 until the end of 2001.

Researchers report mixed evidence on this issue. Some find supporting evidence for the claims of trade-unions. Stewart (2007) concludes that low-wage employment is no springboard to high-wage jobs and that acts as the main conduit for repeat unemployment in the UK. Uhlendorff (2006) finds a strong link between low pay and unemployment in Germany. If the focus is not on low pay, but on temporary jobs, as in this article, Gagliarducci (2005) and García Pérez and Muñoz-Bullón (2007) show that the probability of moving into regular employment decreases with job interruptions and repeated temporary jobs in Italy and in Spain. In contrast, Booth et al. (2002), Zijl et al. (2004), Ichino et al. (2008), and Picchio (2008) report that temporary jobs can indeed be stepping stones to permanent employment in Britain, the Netherlands, and Italy. Finally, Kvasnicka (2008) finds no empirical support for or against the stepping stone hypothesis on German data.

We study this research question on the basis of a new approach. In the literature the stepping stone hypothesis is studied by distinguishing between the type of contract, temporary or permanent, in which workers are hired. We propose a strategy that allows testing the stepping stone hypothesis of temporary jobs without requiring information on the type of contract, information that is lacking in our data. Moreover, we claim that, apart from the lower informational requirement, our strategy has additional advantages over the traditional approach. First, the duration stipulated in the labour contract is not a perfect predictor of the effective job duration, since workers are still possibly dismissed shortly after being recruited. As a consequence, a permanent contract is not a guarantee of a long lasting employment relation, which is *in fine* the outcome which workers care about (Origo and Pagani 2008). Second, temporary contracts may still be relatively long lasting.[1] Then, if this is the case, temporary workers may have the time to invest in human capital and it may not be surprising to find that temporary jobs are springboards to permanent jobs and not "dead-end" positions. A strong case for the stepping stone hypothesis can therefore only be made if it is found even if one enters very short-term jobs. That is why we restrict short-term jobs to those not lasting more than one quarter.[2]

The estimation of the stepping stone effect within this new framework is realized in two steps. First, we estimate the complete labour market trajectory of all sampled workers. Subsequently, we investigate whether the workers who entered short-term jobs are more or less likely to have entered a long-term job than if they had only accepted jobs that last more than one quarter. Since the latter outcome is a counterfactual which is a complicated function of the estimated parameters, we can only find an answer to this question on the basis of simulations. Note that these simulations do not only identify the average treatment effect on the treated (ATT), but also the distribution of the individual treatment effects (Heckman et al. 1997). This allows to verify how the ATT varies with individual characteristics and whether the ATT conceals opposite effects for certain subpopulations.

The credibility of this new approach crucially hinges on the realism of the model in the first step. If we aim at identifying a stepping stone effect, it is essential that the model describing the labour market transition process allows current transitions to be influenced by the type and duration of labour market states occupied in the past. A delayed departure from unem-

[1] In the late 1990s, most of the OECD countries had no limits on the maximum duration and number of renewals of temporary jobs (OECD 1999, § 2).

[2] One may criticize our approach in that one cannot base policy advice on a job classification that depends on realised spell duration, since one does not know, at the moment of hiring, how long a job will last. As a matter of fact, the short-term jobs as defined in this paper may be permanent jobs that end prematurely. As a consequence, finding a stepping stone effect with our definition should be less likely than if we had used a contract type classification, since prematurely ended permanent contracts would then be identified as successful. Therefore, if, on the basis of this criticism, one prefers the traditional approach, then again our estimates provide a lower bound to the stepping stone effect.

ployment may indeed lead to a deterioration of human capital (Phelps 1972), generate stigma effects (Lockwood 1991, Pissarides 1992), or convey a signal of inferior worker quality (Gibbons and Katz 1991) and thereby reduce the length of the subsequent job spell. On the other hand, by postponing the exit from unemployment one may improve the job match quality (Marimon and Zilibotti 1999). Similarly, directly related to the stepping stone hypothesis, workers may signal their motivation by the mere acceptance of jobs, independently of whether they are short- or long-term, and thereby enhancing their future employment prospects. However, short-term jobs may also lead to less investment in human capital or may signal low productivity, decreasing thereby the chance of a long-lasting employment relationship.

In order to accommodate the aforementioned concerns, we estimate a multi-spell mixed proportional hazard (MPH) model with competing risks of exit in which we allow lagged occurrence and duration dependence. We distinguish between three states: unemployment, employment in the same firm and an absorbing censoring state. We explicitly model job-to-job transitions. In order to identify a true stepping stone effect, the model needs to account for a potential selection bias: workers entering a short-term job are not comparable to those who remain unemployed. The literature has followed two main approaches to deal with this problem: the propensity score matching approach (Ichino et al. 2008), which accounts only for selection on observables, and the "timing of events" approach formalized by Abbring and van den Berg (2003b), which allows temporary workers to be different in terms of unobserved characteristics as well. Our approach is closely related to the latter. The selection on unobservables is controlled for on the basis of a discrete distribution with an unknown number of mass points in which the correlation structure is completely flexible (Heckman and Singer 1984, Gaure et al. 2007). Extending the proofs of Honoré (1993) and Abbring and van den Berg (2003a), Horny and Picchio (2008) prove that, if one imposes the MPH structure, the heterogeneity distribution is non-parametrically identified together with the structural parameters of the model, including the lagged occurrence and duration dependence. Moreover, since we observe multiple spells in this empirical application, we expect that one can prove, by extending the results for the single destination model (Heckman and Singer 1984), that the model is over-identified and that the proportionality assumption can be relaxed.

In a multiple spell model with a dynamic structure it is essential to correctly specify the initial conditions. This task is simplified since the sample consists of school-leavers without any previous labour market experience. However, one complication has to be dealt with: all school-leavers have been nine months unemployed at the start of the observation period. We correct for the selectivity induced by this stock sampling on the basis of a conditional likelihood approach proposed by Ridder (1984). Moreover, in a robustness analysis we show that the restrictions imposed by this approach cannot be rejected against a non-nested more general solution to this problem (Heckman 1981, Gritz 1993).

The article is organized as follows. The data and the sample are described in section 2. Section 3 discusses the specification of the econometric model. The estimation results are reported and commented in section 4. Section 5 deals with simulations, by way of which we assess the goodness of fit of the model and we evaluate whether short-term jobs are springboards to long-term jobs. Section 6 concludes.

2 The Data

The empirical analysis is conducted by using administrative records gathered by the Crossroads Bank for Social Security (CBSS).[3] The CBSS merges data from the different Social Insurance institutions in Belgium and allows thereby to construct the quarterly employment history of all Belgian workers. As explained in the Introduction, this research is concerned with disadvantaged youth. To this purpose we sampled all Belgian school-leavers, aged between 18 and 25 years, who, in 1998, were still unemployed nine months after graduation. In Belgium, after this "waiting period" of nine months, these school-leavers are entitled to unemployment benefits (UB) and, as a consequence, they show up for the first time in the administrative records of the CBSS.[4] By sampling from a population of school-leavers we drastically simplify initial condition problems in the analysis of lagged labour market dependence below, 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 does complicate the analysis somewhat. We will discuss in subsection 3.3 how we will deal with this complication.

The eventual sample contains 8,921 women and 6,627 men. The administrative records allowed us to reconstruct the quarterly (un-)employment history of these workers for a period of (maximum) four years, from the beginning of 1998 until the end of 2001. In the analysis we distinguish three mutually exclusive labour market states occupied at the end of each quarter:

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

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

unemployed as UB recipient (u), employed (e), and an absorbing censoring state (a). This censoring state is accessed if the worker leaves the labour force, enters a training programme, returns to school, or if the individual is sanctioned and loose her entitlement to UB. We consider five possible transitions between these states: (u, e), (u, a), (e, u), (e, a) and, since the data contain a firm indicator, job-to-job transitions (e, e) can be identified as well.

Table 1 reports descriptive statistics about the number of spells observed for each individual. Individuals occupy on average 2.5 different labour market states during the four year observation window and a maximum of 12. Men are more mobile than women: 39% of the men sample experience at least 3 spells, whereas only 33% of the women. This multi-spell information is exploited to infer the impact of the lagged labour market outcomes on the subsequent transition intensities. Figure A-1 in appendix A-2 reports, by gender, the number of transitions that are observed in the data.

Table 1: Individual Observations by Number of Observed Spells and Gender

Number of spells (Unemployment + job spells)	Male		Female	
1	6,627	100.0%	8,921	100.0%
2	3,901	58.9%	4,405	49.4%
3	2,552	38.5%	2,917	32.7%
4	1,513	22.8%	1,755	19.7%
5	876	13.2%	1,028	11.5%
6	492	7.4%	577	6.5%
7	265	4.0%	326	3.7%
8	132	2.0%	181	2.0%
9	70	1.1%	95	1.1%
More than 9	49	0.8%	70	0.8%
Total observed spells	16,477		20,275	
Average spells per individual	2.49		2.27	
Maximum number of individual spells	12		12	

Table 2 displays summary statistics for the explanatory variables contained in the data. These can be decomposed into three groups: time-invariant covariates fixed at the sampling date, spell specific variables fixed at the value attained at the start of the labour market spell, but varying across spells, and time-varying covariates which values can change every quarter. The statistics of spell specific and time-varying explanatory variables are reported at the sampling date, except for the firm characteristics, which are reported at the start of the first job spell. Summary statistics of time-varying variables fixed at the beginning of subsequent labour market spells are reported in appendix A-2, Table A-1.

Nationality, region of residence, and education are the time-invariant covariates. Since the sample consists of long-term unemployed, sections of the

Table 2: Summary Statistics by Gender

	Male		Female	
	Mean	St.Dev.	Mean	St.Dev.
Time-invariant covariates				
Nationality				
Belgian	.891	.312	.879	.326
Non-Belgian EU	.052	.221	.054	.226
Non EU	.057	.233	.067	.250
Education				
Primary (6 to 9 years of schooling)	.121	.326	.079	.269
Lower secondary (9 to 12 years)	.280	.449	.226	.419
Higher secondary (12 to 16 years)	.422	.494	.481	.500
Higher education (16 years or more)	.126	.331	.173	.378
Other	.009	.095	.008	.088
Unknown	.042	.201	.033	.178
Region of residence				
Flanders	.201	.400	.245	.430
Wallonia	.674	.469	.641	.480
Brussels	.125	.331	.114	.317
Time-variant spell-specific covariates at sampling date				
Age	20.5	1.96	20.4	1.97
Monthly unemployment benefits (in €)	332.9	120.5	344.0	139.0
Quarter of entry				
January-February-March	.081	.272	.071	.258
April-May-June	.660	.474	.689	.463
July-August-September	.166	.372	.164	.371
October-November-December	.093	.290	.076	.264
Household Position				
Head of household	.077	.266	.108	.311
Single	.134	.341	.101	.302
Cohabitant	.789	.408	.791	.407
Firm size				
$[1, 20)$ employees	.272	.445	.254	.435
$[20, 50)$ employees	.063	.243	.071	.257
$[50, 100)$ employees	.044	.205	.044	.205
$[100, 500)$ employees	.135	.342	.142	.349
500 or more employees	.486	.500	.489	.500
Sector				
Agriculture	.029	.168	.018	.133
Industry & Mining	.086	.281	.039	.193
Building & Energy	.082	.274	.011	.103
Wholesale & Retail trade	.164	.370	.183	.387
Credit & Insurance	.014	.119	.017	.130
Business services	.420	.494	.343	.475
Other services & Public admin.	.205	.403	.390	.488
Time-variant covariates at sampling date				
Local unemployment rate	.184	.069	.269	.085
Observations	6,627		8,921	

population with a high unemployment risk are more represented in the sample than in the population as a whole: foreigners, lowly schooled youth and, since the unemployment rate in Flanders is much lower, those living in Wallonia and Brussels. The high share of youth living in Wallonia is especially striking: roughly two thirds of the sample lives in Wallonia, whereas only one third of the total Belgian population has its residence in Wallonia.

The set of spell specific explanatory variables contains age, quarter of entry into the spell, household position, the monthly amount of unemployment benefits (if the origin state is u), and a set of sector and firm size indicator variables (if the origin state is e). Two variables are conditioned upon in the empirical analysis, but not reported in Table 2 since their value is zero at the sampling date: the length of the previous labour market spell, an indicator whether the previous spell was an unemployment event. The sampled individuals are 20.5 years old on average.

We distinguish between three types of household positions: head of household, single or cohabitant. These categories determine together with age the level of the flat UB rate to which the unemployed school-leavers are entitled to after the higher mentioned waiting period. In 2000, the monthly benefit level varied between 307€ for cohabitants (more than 18 years old) not in charge of other members in the household and 790€ for household heads. The majority of the sampled individuals (79%) is cohabitant. This reflects that most youth is still living in their parents' home.

School-leavers who worked at least one year during a time window of 18 months are entitled to higher benefits if they are laid off.[5] There are some workers in the sample who are indeed paid these higher UB's when they experience a subsequent unemployment spell. In order to account for the adverse incentive effects related to these higher benefit levels, we explicitly included the monthly UB level as an explanatory variable. In addition, we explicitly take into account that, if one is not the head of the household, this higher UB drops to a lower level after one year. As a consequence, to the extent that this drop is anticipated, this affects the profile of the duration dependence of the transition rate from unemployment. Following Meyer (1990) we explicitly control for this by including four time-varying indicator variables (not reported in Table 2). If τ denotes the number of quarters remaining before benefits fall to a lower level, we define these variables as follows: $UI\ 1 = 1$ if $\tau = 1$, and 0 otherwise; $UI\ 2 = 1$ if $\tau \leq 2$, and 0 otherwise; $UI\ 3 = 1$ if $\tau \leq 3$, and 0 otherwise; $UI\ 4 = 1$ if $\tau \leq 4$, and 0 otherwise. In the empirical analysis below the coefficient of $UI\ 1$ captures the marginal effect of going from 2 quarters to 1 quarter before the benefit drop. The coefficients of the

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

other variables have a similar interpretation.

The firm size indicators are created on the basis of the number of employees in the reference worker's firm. We distinguish five firm size types. Almost one half of the subsample of those who find a job are employed in large firms and more than one quarter in small firms. On the basis of the NACE nomenclature[6] and a 2-digit information, we distinguish seven firm sectors. Looking at the distribution of workers over sectors, it is noted that most of them is employed in the category "Business services" which comprises heterogeneous types of services for firms: cleaning services, call-center activities, labour recruitment, counselling, advertising, and accounting.

Finally, in order to take business cycle effects into account, the local unemployment rate is modelled as a time-varying explanatory variable. Since in Belgium no statistic exists on the local unemployment rate following the standard ILO definition, we rely on a non-standard statistic provided by the Belgian Unemployment Agency (ONEM). This statistic reports the fraction of the population insured against the risk of unemployment (thereby excluding civil servants) which is entitled to UB. This usually results in a higher unemployment rate than the one obtained with the ILO definition. At the sampling date in 1998, the average local unemployment rate for men and women is 18.4% and 26.9%, compared to 7.7% and 11.6% according to the standard ILO definition (http://epp.eurostat.ec.europa.eu).

3 The Econometric Model

In the Introduction we announced that the analysis in this paper is conducted in two steps. In a first step we estimate a multi-state multi-spell duration model in which the nature and the duration of the labour market states occupied in the past are allowed to influence the duration of stay in the current state. In a second step (Section 5), we run a simulation exercise on this econometric model to identify whether temporary jobs are stepping stones to long-term jobs. This section discusses the identification of the structural parameters of interest, makes the model specification explicit, and elucidates the main steps in the construction of the likelihood function.

3.1 Identification

In order to determine the stepping stone effect of temporary jobs we must have a model that credibly identifies the causal impact of the labour mar-

[6]See http://ec.europa.eu/comm/competition/mergers/cases_old/index/nace_all.html for a detailed list of NACE codes.

ket history on the current labour market trajectory. The determination of this causal impact crucially depends on the capacity to control for sources of endogeneity. We attempt to control for four sources of endogeneity: (i) unobserved heterogeneity; (ii) endogenous censoring; (iii) endogeneity induced by time-varying variables; (iv) initial conditions.

It is well known that the failure to control for (un)observed individual characteristics leads to inconsistent estimates of the structural parameters of interest, in particular of the baseline hazard and the lagged occurrence and duration dependence. Recently, Horny and Picchio (2008) show, extending the proofs of Honoré (1993) and Abbring and van den Berg (2003a), that, if one imposes the mixed proportional hazard (MPH) structure on the transition intensities, the multivariate heterogeneity distribution of the unobserved variables affecting the transitions between all states is non-parametrically identified together with the structural parameters of the model, including the lagged occurrence and duration dependence. In addition, on the basis of the results of Honoré (1993) for single exit models and Abbring and van den Berg (2003a) for competing risks models, we conjecture that in a framework with multiple unemployment and job spells the MPH assumption can be relaxed. Nevertheless, we impose the MPH specification throughout the analysis.

In the determination of a stepping stone effect, we focus on the transitions between two labour market states: unemployment (u) and employment (e). However, as pointed out by van den Berg et al. (1994) and van den Berg and Lindeboom (1998), if there are unobserved characteristics affecting both the labour market transitions of interest ((u, e), (e, u) and (e, e)) and the transitions to other destinations, this may lead to inconsistent estimates of the parameters determining the transitions of interest. This is why we explicitly specify an absorbing censoring state (a) the transitions to which ((u, a) and (e, a)) may depend on an unobserved variable that is correlated with the other unobservables.

In the two preceding points we discussed how we can correct for the selectivity bias induced by time-constant determinants of the labour market transitions. Event history models can, however, also easily take time-varying factors of transitions into account if their time-path is observed. In the previous section we discussed which time-varying variables we condition upon in the analysis and why.

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

We compare two solutions to this problem: the conditional likelihood approach proposed by Ridder (1984) and the approximate solution suggested by Heckman (1981) for dynamic discrete choice models implemented by Gritz (1993) in a duration model. We prefer these approaches to the more efficient method followed by Flinn and Heckman (1982), since they are more robust by not requiring the strong assumptions that the economic environment is stationary and in equilibrium. Heckman's (1981) solution is more flexible than Ridder's (1984), but, as explained below, we prefer the latter to the former, since in Heckman's approach one looses the structural interpretation of the parameters regarding the first transition from unemployment and hence these are no longer comparable to the second transition from unemployment. This choice is justified on the basis of a Vuong (1989) test of strictly non-nested models: neither model can be rejected against the other according to this test. We will show in more detail below how these initial conditions modify the likelihood function.

3.2 The Specification

Since we only observe the labour market state occupied at the end of each quarter, the observed data are grouped in discrete time intervals. However, in order to avoid the dependency of parameters to the time unit of observation (Flinn and Heckman 1982), we follow van den Berg and van der Klaauw (2001) and specify the discrete-time process as in a grouped continuous-time model. The transition intensity in spell s from the origin state j to the destination state k is denoted by θ^s_{jk}, with the ordered pair $(j,k) \in \mathscr{X} = \{(u,e),(u,a),(e,e),(e,u),\ (e,a)\}$. During spell s started at time τ_s (with $\tau_s \in \mathbb{N}_0$) and after t_s quarters in state j (with $t_s \in \mathbb{N}_0$), the transition intensity from j ot k is specified in the following MPH form:

$$\theta^s_{jk}(t_s|\mathbf{x}_{jk}(\tau_s+t_s),v_{jk}) = \exp\{\gamma_{jk}(t_s)+\boldsymbol{\beta}'_{jk}\mathbf{x}_{jk}(\tau_s+t_s)\}v^s_{jk} \tag{1}$$

for $(j,k)\in\mathscr{L}$, where $\exp[\gamma_{jk}(t_s)]$ is the piecewise constant baseline hazard capturing the duration dependence; v^s_{jk} is the spell- and transition-specific individual heterogeneity, a positive random number; $\mathbf{x}_{jk}(\tau_s+t_s)$ is a K_{jk} dimensional vector of time-invariant and time-variant covariates controlling for observed heterogeneity at the transition quarter (τ_s+t_s) and including the length and type of the preceding labour market spell. The associated and conformable parameter vector to be estimated is $\boldsymbol{\beta}_{jk}$.

Note that we impose in (1) that $\gamma_{jk}(t_s)$ and $\boldsymbol{\beta}_{jk}$ are fixed across spells. This is not required for identification (Horny and Picchio 2008), but it reduces the computational burden, increases the precision of the parameter estimates and, by imposing more structure, intuitively, identification will depend less on the imposed MPH specification. In fact, we restrict the specification even further such that the transition intensities are just shifted proportionally across subsequent spells or even not at all if the absorbing censoring state (a) is the destination. We impose

(i) $v^s_{ja}=v_{ja}$ for $j=u,e$ and $s=1,\dots,S$;

(ii) $v^s_{jk}=v_{jk}c^s_{jk}$, for $(j,k)\in\{(u,e),(e,e),(e,u)\}$, where $c^s_{jk}=c^3_{jk}$ for $s=4,\dots,S$. The scaling factors c^1_{jk} are normalized to 1 for each $(j,k)\in\{(u,e),(e,e),(e,u)\}$.

To avoid parametric assumptions on the distribution of the unobserved heterogeneity, we follow Heckman and Singer (1984) and assume that the vector $\mathbf{v}\equiv[v_{ue},v_{ua},v_{ee},v_{eu},v_{ea}]$ is a random draw from a discrete distribution function with a finite and (a priori) unknown number M of support points. The probabilities associated to the mass points sum to one and, $\forall\ m=1,\dots,M$, are denoted by

$$p_m=\Pr(v_{ue}=v_{uem},v_{ua}=v_{uam},v_{ee}=v_{eem},v_{eu}=v_{eum},v_{ea}=v_{eam})\equiv\Pr(\mathbf{v}=\mathbf{v}_m)$$

and specified as logistic transforms:

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

A pre-specified low number of support points may result in substantial bias. We therefore choose, as suggested by the Gaure et al.'s (2007) Monte Carlo simulations, the M number of support points to minimize the Akaike Information Criterion (AIC).

3.3 The Likelihood Function

In the derivation of the likelihood we first ignore the initial conditions problem and assume that the sample is drawn at the start of the unemployment spell right after graduation. In a second step, we explain what we should modify to take into account that all workers are already three quarters unemployed at the sampling date.

We start with the derivation of the individual contributions of each spell to the likelihood function. The contribution of a spell s with origin state j that is incomplete because it is right censored at the end of the observation period is simply given by the survivor function in the given labour market state until the end of the observation period:

$$L^c_{is}(t_s|\mathbf{x}_j, \mathbf{v}^s_j; \Theta_j) \equiv S_j(t_s|\mathbf{x}_j, \mathbf{v}^s_j) = \prod_{d=1}^{t_s} \exp\{-\sum_{(j,k)\in\mathscr{J}} \theta^s_{jk}(\tau|\mathbf{x}_{jk}(\tau_s+d), v^s_{jk})\} \quad (2)$$

where $\mathscr{J} = \mathscr{E} \equiv \{(e,e),(e,u),(e,a)\}$ if $j=e$ and $\mathscr{J} = \mathscr{U} \equiv \{(u,e),(u,a)\}$ if $j=u$, Θ_j is the set of parameters if the origin state is j, and $\mathbf{x}_j$ and $\mathbf{v}^s_j$ collect the $\mathbf{x}_{jk}(\tau_s+t_s)$'s and the v^s_{jk}'s with $(j,k)\in\mathscr{J}$.

Using the same notation, the contribution to the likelihood function of a complete spell s with origin state j and destination state k is derived in appendix A-1 and takes the following form:

$$\begin{aligned} L_{is}(t_s|\mathbf{x}_j, \mathbf{v}^s_j; \Theta_j) &= \frac{\theta^s_{jk}(t_s|\mathbf{x}_{jk}(\tau_s+t_s), v^s_{jk})}{\sum_{(b,c)\in\mathscr{J}} \theta^s_{bc}(t_s|\mathbf{x}_{bc}(\tau_s+t_s, v^s_{bc})} \\ &\times \left[S_j(t_s-1|\mathbf{x}_j, \mathbf{v}^s_j) - S_j(t_s|\mathbf{x}_j, \mathbf{v}^s_j)\right] \end{aligned} \quad (3)$$

Conditional on the unobserved covariates, individual i's contribution to the likelihood function is given by the product over the individual i's single spell contributions. Let $L_i(\mathbf{t}_i|\mathbf{x}_i, \mathbf{v}; \Theta)$ denote this product, where $\mathbf{t}_i$ collects all the individual i's labour market durations and $\mathbf{x}_i$ and $\mathbf{v}$ the associated set of observed and unobserved covariates. Integrating out the unobserved heterogeneity $\mathbf{v}$ on the basis of the above-mentioned discrete distribution yields the unconditional individual contribution to the likelihood function:

$$L_i(\mathbf{t}_i|\mathbf{x}_i; \Theta) = \sum_{m=1}^{M} p_m L_i(\mathbf{t}_i|\mathbf{x}_i, \mathbf{v}_m; \Theta). \quad (4)$$

The log-likelihood function sums the logarithm of this expression over all the individuals in the sample.

We now turn to the modification required to deal with the initial condition problem. Ridder (1984) considers the likelihood conditional on being observed at the sampling date. The probability of being observed at the sampling date is given by the joint probability of entering unemployment after graduation and remaining unemployed during the subsequent three quarters. The probability of entry into unemployment can, however, be ignored if we assume that it is proportional in observed and unobserved characteristics. The required modification is therefore just a division of the individual contribution in (4) by the probability of surviving three quarters in unemployment:

$$L_i^0(\mathbf{t}_i|\mathbf{x}_i;\Theta) = \frac{L_i(\mathbf{t}_i|\mathbf{x}_i;\Theta)}{\sum_{m=1}^{M} p_m S_u(3|\mathbf{x}_u, \mathbf{v}_u^1)}. \tag{5}$$

The correction for initial conditions is carried out by the presence of S_u in the numerator and denominator of (5): it corrects for different unobserved propensities to leave among different subpopulations and ensures thereby that, conditional on this differential sorting, the impact of observed characteristics remains proportional with duration.

Heckman's (1981) approximate solution to the initial conditions boils down construct the likelihood on the basis of individual contributions of the form expressed in (4) in which the parameters of the transition intensities from the first unemployment spell, θ_{uj}^1 and θ_{ua}^1, are no longer constrained to be equal to those from the subsequent unemployment spells.[7] The drawback of this approach is that the estimated transitions from the first unemployment spell approximate those of the stock sample and do not therefore have a structural interpretation.

4 Estimation Results

We focus the discussion of the estimation results on those factors that matter for the determination of the stepping stone effect of short term jobs: current duration dependence and lagged occurrence and duration dependence related to the transitions between the two labour market states of interest: u and e. Since the parameters determining the transition intensities to the absorbing censoring state a are not of direct interest, they are reported in the appendix.

The main results discussed in this section are based on Ridder's (1984) proposed correction for initial conditions. On the basis of a Vuong (1989) test, modified to permit AIC log-likelihood penalties, we cannot reject this benchmark model against one based on a Heckman (1981) approach at a

[7]Note that the baseline transition intensities of the first three quarters are not identified, since no-one in the sample leaves unemployment within the three first quarters.

p-value of 0.305 for men and 0.140 for women. Moreover, as can be verified in Table A-7 in appendix A-2, the parameter estimates of interest regarding the lagged duration and occurrence dependence are in line with those of the benchmark model.

Figure 1 displays the patterns of the duration dependence of three transition rates: (u, e), (e, e) and (e, u).[8] The baseline transition from unemployment to employment, reported in the upper panel, exhibits strong negative duration dependence up to the 7th quarter and is roughly constant thereafter. This contrasts with the results of Cockx and Dejemeppe (2005), who cannot reject for young men aged 28 years or younger a constant profile of the baseline hazard rate from unemployment. However, this finding could follow from their incapacity to distinguish between transitions to employment and to other destinations: even if parameter estimates are not very precise, Table A-2 in appendix A-2 reports that the baseline transition rate to the absorbing censoring state a is, if anything, increasing with unemployment duration.

The negative duration dependence of the transition rate to employment implies that the worker has an interest to accept job offers as soon as possible, since his chances to find a job diminish as time goes by. This finding corroborates the stepping stone effect of temporary jobs.

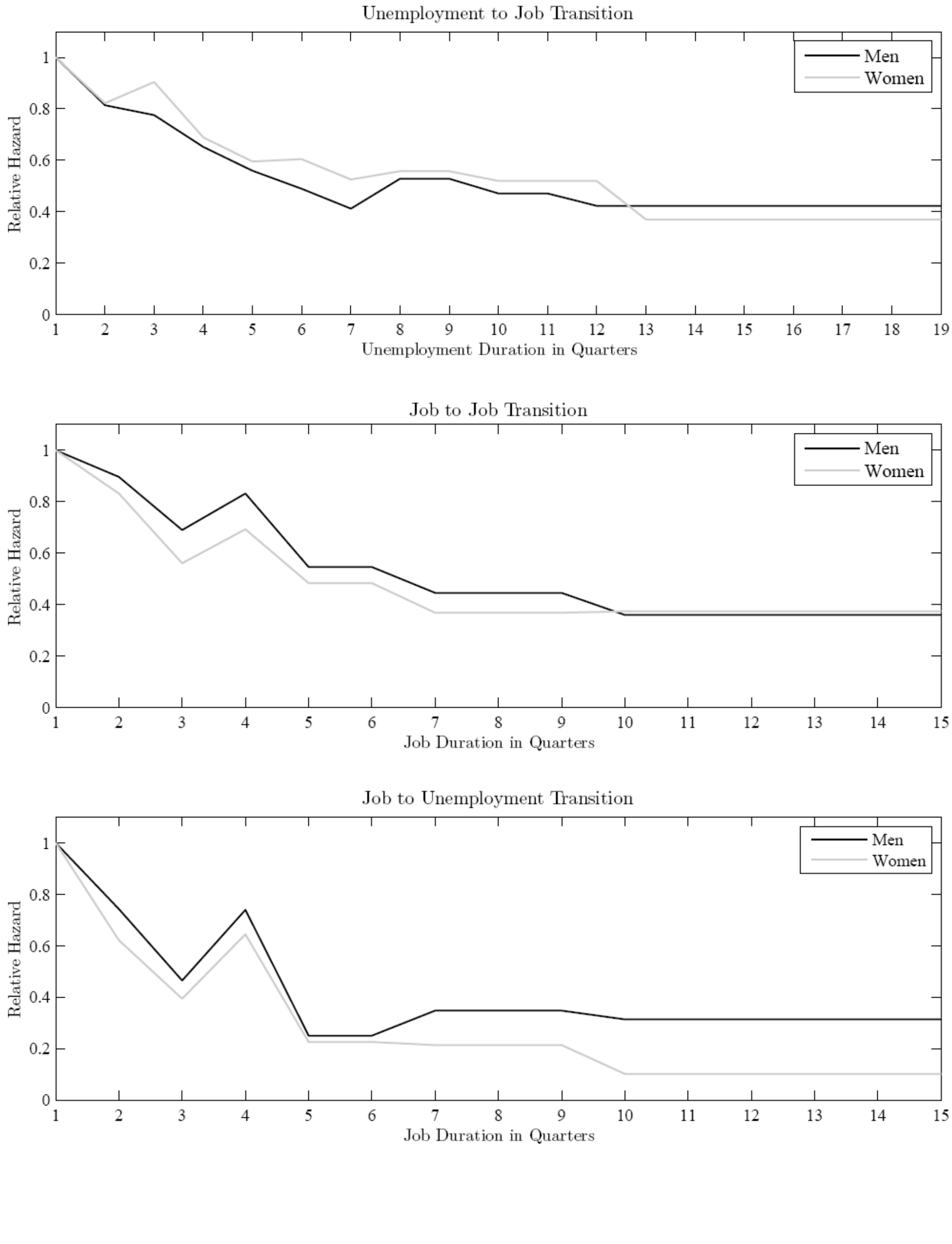
The bottom panels of figure 1 depict the duration profiles of e-e and e-u transition intensities. Both display that the job separation rate declines with tenure, a finding that is consistent with the central facts about working mobility (e.g. Topel and Ward 1992, Farber 1999). The spike in the fourth quarter is probably related to the non-renewal of temporary contracts that typically last one year. The transition rate to unemployment declines more and much faster than the job-to-job transitions. It stabilises after 5 quarters, whereas the job-to-job transitions continue to decline gradually. This means that dismissals essentially occur during the first year, whereas job changes are spread out over a longer time span.

The theoretical literature argues that the presence and length of a previous job affects the speed at which a laid-off worker is re-employed. On the one hand, laid off workers with (longer) job tenure face a higher loss of specific human capital and raise their reservation wages in order to restart the career from the level attained before their dismissals (Ljungqvist and Sargent 1998). This slows down the re-employment rate. On the other hand, dismissed workers with (longer) tenure may signal more motivation (devotion to his job) or may have lost less (accumulated more) general human capital, which make them more attractive to be rehired (Lockwood 1991).

Columns (1) and (2) of Table 3 report evidence that is essentially in

[8]The point estimates and standard errors are reported in Table A-2 in appendix A-2.

Figure 1: Estimated Baseline Hazards by Gender



line with the second theoretical explanation. Having work experience is what matters. Youth with work experience are much more likely to be re-employed than youth without such experience. Work experience raises the re-employment rate by 75% for women and 38% for men.[9] The length of the job barely matters. The coefficient of lagged job tenure is very close to zero and insignificant for men and for women it is slightly negative, but only significant at 10%. This is again evidence that shows that it is not a good idea to reject short-term jobs to have more chances of finding a long-term job.

Table 3: The Impact of the Past on Transition Intensities by Gender

Transition	(u,e)		(e,e)		(e,u)	
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Men						
Lagged unemployment duration	–	–	-.031**	.014	-.019	.013
Previous state: unemployment	–	–	-.146	.100	.237*	.130
Lagged job tenure	-.004	.023	-.028	.023	-.127***	.037
Scaling factors – $\ln c^1_{jk}$s normalized to zero						
$\ln c^2_{jk}$	.319***	.102	-.161	.129	-.005	.142
$\ln c^3_{jk}$	.532***	.113	-.030	.106	-.362***	.106
# of observations	6,627		# of spells		16,447	
# of parameters	191		Log-likelihood		-41,174.1	
Women						
Lagged unemployment duration	–	–	-.041***	.015	-.030**	.012
Previous state: unemployment	–	–	-.017	.104	.302**	.120
Lagged job tenure	-.032*	.019	-.042**	.020	-.063**	.029
Scaling factors – $\ln c^1_{jk}$s normalized to zero						
$\ln c^2_{jk}$	.560***	.100	-.044	.124	-.251*	.134
$\ln c^3_{jk}$	.683***	.109	-.109	.101	-.319***	.094
# of observations	8,921		# of spells		20,275	
# of parameters	197		Log-likelihood		-51,269.2	

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

Columns (3)–(6) of Table 3 inform us on the impact of recent labour market history on job stability. The evidence confirms that also here it is past work experience that matters, but the length of the previous job is more important here. First, if a worker entered a job from unemployment instead of coming from another job, the chances of becoming unemployed increase by 27% for men and by 35% for women.[10] In addition, the number of jobs experienced in the past reduces the transition rate to unemployment: relative to those without any past work experience, this transition rate is 30%

[9] $75 = [\exp(.560) - 1] \cdot 100$ and $38 = [\exp(.319) - 1] \cdot 100$.

[10] $27 \approx [\exp(.237) - 1] \cdot 100$ and $35 \approx [\exp(.302) - 1] \cdot 100$.

lower for men and 27% for women with more than two job experiences in the past.[11] In contrast, job-to-job transitions are not significantly influenced by the nature of the past labour market state. Second, the longer is the preceding job, the less likely the worker is dismissed: increasing lagged job tenure by one quarter decreases the current job-to-unemployment transition intensity by 12% for men and 6% for women.[12] For women, but not for men, this also decreases the job-to-job transitions by 4%.

The theoretical explanation for this finding is similar to the one advanced for the previous findings. Those with previous job experience signal motivation and devotion or have acquired more general skills and this reduces the chances of lay-off or of continuing search to find a better job match. In contrast, in relation to the main research question, evidence is more mixed. On the one hand, in terms of job stability it is better to have acquired past work experience rather than not, and the more jobs occupied in the past, the stabler the job. In contrast, shorter-term jobs increase the likelihood of dead-end positions or of cycling between unstable jobs (for women only).

Finally, the first line of each panel in Table 3 informs us whether lagged unemployment duration has a scarring effect on the stability of the subsequent job. If long-term unemployed workers are excluded from the primary market and are forced to look for a job in a secondary labour market characterized by short-term and dead-end positions then a scarring effect of unemployment duration may result (Piore 1971, Pissarides 1992, Pissarides 1994). However, it has also been argued than longer job search may lead to a better match quality that is less likely to be dissolved (Burdett 1979, Marimon and Zilibotti 1999).

The empirical results are in accordance with the second explanation. The point estimates indicate that for women one more quarter of unemployment reduces the job destruction rate by 3% and the job-to-job transition intensity by 4%. For men only the job-to-job transition rate falls significantly by 3% per quarter of unemployment. This finding suggests that an unemployed worker may have an interest in postponing job acceptance, since by doing so she increases the likelihood of entering a long-term job.[13] However, we have seen that other factors act in the opposite direction. In order to conclude which factor dominate and to quantify the effect we carried out a simulation reported in Section 5.

[11] $30 \approx [1 - \exp(-.362)] \cdot 100$ and $27 \approx [1 - \exp(-.319)] \cdot 100$.

[12] $12 \approx [1 - \exp(-.127)] \cdot 100$ and $6 \approx [1 - \exp(-.063)] \cdot 100$.

[13] Similar findings are pointed out by Belzil (2001) for Canada and Tatsiramos (2004) for France and Germany. Evaluating the impact of UB in terms of their durations respectively on job and employment stability, they find that additional time in unemployment lowers the job and employment hazard rates for UB recipients.

Finally, we briefly comment on the other estimated coefficients reported in Tables A-3 and A-5 in appendix A-2. First, the estimated coefficients of most of the observed explanatory variables are in line with expectations. The only dissonance concerns the impact of the UB. For men the level of UB has, as expected, a large and significantly negative impact on the transition rate from unemployment to employment. However, for women this impact is large and significantly positive. To understand this, we need to recall our discussion in Section 2, where we explained that this coefficient is only identified on the basis of those young workers who have acquired a sufficiently long (more than one year) work experience during the observation period. A second point is that the empirical analysis does not control for the wages earned by these workers. Since the level of UB is (within a range) proportional to wages, a higher level of UB may also reflect a higher wage level and, consequently, a higher productivity level. This may explain the counterintuitive finding for women. With regards the anticipation effect of the drop in the benefit level, we do not find clear evidence in line with theory, but this can be due to the fact that these effects are identified on a relatively small population: The coefficients are unstable and measured with little precision.

Second, the estimated probability masses and the location of each mass point suggest an important diversity in the impact of unobserved characteristics on the transition intensities. The discrete distribution function of the random variable $\mathbf{v}$ is found to have 4 probability masses for men and 5 for women. When an heterogeneity point was estimated to be a large negative number, it was fixed to avoid numerical problems (Gaure et al. 2007) and reported as $-\infty$ in tables A-4 and A-5.

5 Simulations

In order to assess the goodness of fit of the model and to answer the main question of this paper, we simulated labour market careers using the estimation results of the benchmark model.

There are some issues that have to be dealt with before simulating the model. First of all, each individual in the sample has to be assigned a random vector from the distribution of unobserved heterogeneity. Note that, since we corrected for initial conditions, the distribution of individual heterogeneity conditional on $\mathbf{x}_u$ is given by

$$g(\mathbf{v}_u, \mathbf{v}_e | \mathbf{x}_u; \Theta_u) = \frac{S_u(3|\mathbf{x}_u; \Theta_u, \mathbf{v}_u^1) g(\mathbf{v}_u, \mathbf{v}_e)}{\int_{\Re^5} S_u(3|\mathbf{x}_u; \Theta_u, \mathbf{v}_u^1) g(\mathbf{v}_u, \mathbf{v}_e) d(\mathbf{v}_u, \mathbf{v}_e)}. \tag{6}$$

Hence, we drew, for each individual in the sample, the unobserved heterogeneity vectors of point mass locations $\hat{\mathbf{v}}_m \equiv [\hat{v}_{uem}, \hat{v}_{uam}, \hat{v}_{eem}, \hat{v}_{eum}, \hat{v}_{eam}]$, for $m = 1, \cdots, \hat{M}$ according to the estimated counterpart of (6). This means that the probability p_{im} of individual i of being of type m is estimated, given the discrete distribution assumption and for $m = 1, \ldots, \widehat{M}$, by

$$\hat{p}_{im} = \frac{\widehat{S}_u(3|\mathbf{x}_{ui}; \widehat{\Theta}_u, \hat{\mathbf{v}}^1_{um})\hat{p}_m}{\sum_{r=1}^{\widehat{M}} \widehat{S}_u(3|\mathbf{x}_{ui}; \widehat{\Theta}_u, \hat{\mathbf{v}}^1_{ur})\hat{p}_r},$$

where $\widehat{M} = 4$ for men and $\widehat{M} = 5$ for women.

Secondly, each individual has to be assigned a vector of time-constant individual characteristics. Every observation was simply given his/her own time-constant characteristics observed in the dataset.

Thirdly, spell-specific or time-variant variables, like quarter of entry in the spell, age, and unemployment rate, have been assigned during the simulation process according to the sampling date information and preceding simulated durations. The household position of each individual at the beginning of a simulated labour market spell was chosen by taking the corresponding calendar time household position from the actual dataset. Conditional on household position, we drew the amount of unemployment benefits.

Lastly, at the beginning of each simulated job spell, each worker is given a vector of firm characteristics by drawing it from the set of firm characteristics vectors conditional on lagged labour market duration and state.

At the beginning of the observation period, everyone was unemployed. By sampling design, everyone has, at the sampling date, an ongoing elapsed duration of unemployment equal to three quarters. Therefore, the duration of this first unemployment event was simulated by transition lotteries at each quarter, starting from the fourth quarter. In the fourth quarter, the transition lottery consisted in

- Computing, for each individual, unemployment transition probabilities from the empirical counterparts of the probability of leaving state u for k conditional on surviving one quarter in state u.[14] Since unemployment has two destination states, two transition probabilities had to be computed, π_e and π_a.
- Comparing the transition probabilities of each individual with a random drawing, ξ, from a $[0, 1]$ uniform distribution. A simulated transition to

[14]See equation (A-4) in appendix A-1 for details. In order to take into account of the precision of the estimated coefficients, at each simulation the parameter vector was drawn from a normal distribution with standard deviations computed from the estimated variance-covariance matrix.

e occurred between the fourth and fifth quarter if $0 < \xi < \pi_e$. Similarly, a transition to a occurred if $\pi_e < \xi < \pi_e + \pi_a$. Otherwise, no event occurred and another lottery for the fifth quarter was conducted. The procedure went on until an exit was observed. If no exit was observed before the end of the time window, the spell was right censored.

For individuals who made a simulated transition into a job, we simulated job tenures and job destination states in the same way. We proceeded in simulating labour market careers until the end of the time window for every individual.

When the purpose of the simulation is to provide a goodness of fit measure (subsection 5.1), the time window length of each individual coincides with that observed in the dataset. Data were collected until the end of 2001. Therefore, the time window is 16 quarters long for individuals who entered the sample in January 1998, 15 quarters long if the entrance occurred in April 1998, 14 quarters long if entrance in October 1998, and 13 quarters long if entrance in December 1998.

When counterfactual labour market careers are simulated in order to understand whether short-term jobs are springboards to long-term jobs (subsection 5.2), the time window is 16 quarters for each individual. The extrapolation out of the observed time window is made possible by fixing the household position and the unemployment rate at the last values observed in the dataset.

5.1 Goodness of Fit

Table 4 contrasts the actual unemployment and job duration frequencies with the simulated counterparts and reports simulated confidence intervals.[15] The model perfectly predicts unemployment and job durations for women. Even if for men the model tends to overpredict short labour market spells and the simulated duration frequencies are below the actual ones at long duration, the goodness of fit of both unemployment durations and job tenures is quite satisfactory. In table 5 simulated and predicted duration distributions are disaggregated by labour market spells. It is noted that the model seems to be enough flexible in predicting unemployment durations and job tenures at different points of the labour market career. The overprediction of short unemployment durations for men seems to be the only lack of the model in fitting actual data.

[15]Simulated duration frequencies were obtained by way of 999 simulated labour market careers per each individual in the sample.

Table 4: Simulated and Actual Duration Distributions

	Men				Women			
	Actual frequencies	Predicted frequencies	95% confidence interval		Actual frequencies	Predicted frequencies	95% confidence interval	
Quarters				Unemployment duration				
1	.110	.129	.113	.144	**.111**	.108	.098	.119
2	**.052**	.054	.046	.062	**.048**	.047	.041	.053
3	**.033**	.028	.023	.035	**.030**	.029	.024	.034
4	.126	.138	.128	.148	**.120**	.125	.116	.134
5	**.178**	.182	.171	.194	**.166**	.169	.159	.179
6	**.115**	.113	.104	.123	**.111**	.113	.105	.123
7	**.075**	.071	.064	.079	**.077**	.077	.070	.084
8-9	**.109**	.104	.095	.114	**.107**	.106	.098	.114
10-12	**.087**	.081	.073	.089	**.090**	.090	.083	.097
13-19	.116	.099	.089	.110	**.140**	.137	.126	.146
Quarters				Job tenure				
1	**.384**	.394	.369	.421	**.374**	.384	.366	.401
2	**.169**	.178	.165	.190	**.166**	.166	.155	.178
3	**.095**	.096	.086	.105	**.095**	.094	.085	.103
4	**.086**	.086	.076	.095	**.091**	.087	.079	.095
5-6	**.081**	.079	.070	.088	**.087**	.084	.076	.092
7-9	.094	.083	.074	.093	**.090**	.088	.080	.096
10-15	**.090**	.086	.072	.100	**.097**	.097	.088	.107

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

5.2 Are Short-Term Jobs Springboards to Long-Term Jobs?

By looking at the results in table 3 it was noted that future labour market performances are affected by former labour market occurrences and durations. However, it is not clear what kind of consequences particular events occurring at an early stage of the labour market career can have on future performances of Belgian long-term unemployed school-leavers.

In this subsection we provide a simulation based analysis to infer the effect of accepting a very short-term job at the beginning of the labour market career instead of rejecting it until a stabler job is found. We define short-term job a job that lasts only one quarter. The treatment is the entry into a short-term job at the end of the post-school unemployment event. In a simulation framework, we can simultaneously observe the same person's outocome participating and not participating in the treatment. Thus, at individual level, we contrast the labour market career of those who entered a short-term job after the post-school unemployment event (the treated when treated) with the counterfactual labour market career in the absence of the treatment, i.e. the counterfactual performance when short-term jobs are always rejected (the treated when non treated).

Let us define long-term job a job that lasts at least four quarters. Our

Table 5: Simulated and Actual Duration Distributions by Spells

	Men				Women			
	Actual frequencies	Predicted frequencies	95% confidence interval		Actual frequencies	Predicted frequencies	95% confidence interval	
Quarters	Duration distribution of the 1st unemployment spell							
4	.143	.165	.151	.177	**.135**	.142	.131	.153
5	**.221**	.232	.218	.246	**.205**	.206	.195	.219
6	**.143**	.143	.132	.155	**.138**	.137	.126	.147
7	**.092**	.090	.081	.100	**.093**	.094	.086	.103
8-9	**.136**	.133	.121	.145	**.133**	.130	.120	.140
10-12	**.111**	.104	.094	.115	**.114**	.113	.104	.122
13-19	.155	.133	.120	.147	**.182**	.178	.165	.190
Quarters	Duration distribution of the 1st job							
1	**.368**	.383	.357	.409	**.374**	.374	.353	.395
2	**.166**	.166	.151	.180	**.149**	.156	.143	.170
3	**.090**	.086	.076	.098	**.083**	.086	.076	.097
4	**.089**	.083	.072	.094	.098	.084	.073	.094
5-6	**.067**	.069	.059	.079	**.077**	.074	.064	.084
7-9	**.088**	.082	.071	.093	**.085**	.085	.073	.095
10-15	**.132**	.131	.113	.151	**.135**	.140	.125	.155
Quarters	Duration distribution of the 2nd unemployment spell							
1	.403	.451	.411	.491	**.424**	.418	.384	.451
2	**.194**	.205	.178	.232	**.202**	.197	.172	.224
3	**.131**	.118	.096	.142	**.145**	.129	.107	.151
4	**.085**	.069	.053	.086	**.077**	.073	.058	.089
5	**.057**	.047	.035	.060	**.047**	.054	.042	.067
6	**.033**	.033	.023	.043	.030	.042	.033	.054
7	.033	.021	.014	.029	**.032**	.025	.018	.033
8-9	**.036**	.031	.021	.042	**.025**	.034	.025	.044
10-12	**.026**	.022	.015	.032	.015	.024	.016	.033
13-19	**.001**	.003	.001	.007	**.004**	.003	.001	.006
Quarters	Duration distribution of the 2nd job							
1	**.309**	.328	.289	.368	**.295**	.324	.289	.358
2	**.162**	.168	.145	.191	**.178**	.160	.136	.183
3	**.084**	.099	.082	.118	**.096**	.098	.079	.116
4	**.093**	.094	.077	.113	**.085**	.091	.074	.109
5-6	.123	.099	.080	.118	**.102**	.103	.084	.124
7-9	.144	.117	.094	.139	**.128**	.119	.099	.142
10-15	**.083**	.097	.074	.121	**.116**	.105	.085	.126
Quarters	Duration distribution of the 3rd unemployment spell							
1	.502	.569	.512	.626	**.556**	.523	.469	.576
2	**.228**	.212	.177	.250	**.211**	.198	.168	.232
3	.130	.097	.072	.126	**.094**	.108	.082	.136
4	**.053**	.052	.036	.071	**.064**	.068	.048	.091
5	**.033**	.029	.017	.044	**.029**	.041	.027	.057
6	**.023**	.018	.009	.029	.013	.031	.018	.046
7	**.015**	.009	.003	.017	**.014**	.014	.006	.023
8-9	**.014**	.011	.004	.018	**.013**	.014	.007	.023
10-12	**.001**	.003	.000	.008	**.006**	.004	.001	.008
13-19	**.000**	.000	.000	.000	**.000**	.000	.000	.000
Quarters	Duration distribution of the 3rd job							
1	**.442**	.435	.405	.466	**.405**	.421	.395	.449
2	.178	.197	.179	.214	**.188**	.184	.167	.200
3	**.109**	.107	.093	.120	**.114**	.104	.091	.117
4	**.079**	.087	.074	.100	**.084**	.090	.078	.102
5-6	**.086**	.083	.071	.095	**.095**	.092	.080	.104
7-9	**.081**	.070	.058	.082	**.083**	.080	.070	.093
10-15	**.025**	.022	.016	.028	**.031**	.030	.023	.038

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

causal effect of interest is the difference in the probability of having already entered a long-term job at different quarters after the treatment if treated and non-treated. We try therefore to draw a picture of the short- and medium-term effects of entering a short-term job at the beginning of the labour market career, instead of waiting for a longer lasting job (a job strictly longer than one quarter).

However, in carrying out this evaluation, we have to face problems related to the presence of two possible sources of censoring: i) right-censoring due to the end of the 16 quarters time-window over which simulations are run; ii) endogenous censoring due to a transition from u or e to a.

Right-censoring is faced by focusing on the post-treatment probabilities at selected quarters for those who were treated after a short unemployment duration. By doing so, we have a long enough residual time window over which a medium-term post-treatment evaluation can be carried out, without incurring in right censoring problems.

Endogenous censoring is taken into account by making the estimand of interest conditional on not being endogenously censored yet at the quarter in which the difference in the post-treatment probability of having already entered a long-term job is evaluated.

5.2.1 The Object of Evaluation

Let us denote:

- $S_i \in 5, \ldots, 19$ the quarter in which individual i enters a short-term job after the post-school unemployment event. If such a job is never entered $S_i = \infty$.
- $T_{i|S_i} \in 5, \ldots, 19$ the quarter in which individual i enters a long-term job, given that she/he entered a short-term job in quarter S_i.
- $V_{i|S_i} \in 5, \ldots, 19$ the quarter in which individual i is endogenously censored, given that she/he entered a short-term job in quarter S_i.
- $t = 1, \ldots, M_t$ the post-treatment duration at which we evaluate the difference in the post-treatment probability of having already entered a long-term job if treated and non-treated.
- $s \in 4, \ldots, 19$ the maximum duration of the first unemployment spell (counted from the moment of school departure) in order to be selected in the treatment group. We fix $s = 7$ in order to have a long enough residual time window over which a medium-term post-treatment evaluation can be carried out, without incurring in right censoring problems.[16]

[16] In order to check the robustness of the results to the selection rule we imposed, the

We observe individual i taking treatment, i.e. entering a short-term job, after an unemployment duration S_i when $D_{is} = 1$, where

$$D_{is} = \mathbb{1}(S_i \leq s + 1). \tag{7}$$

The outcome variable is denoted by Y_{iS_it} and is equal to one if individual i has already found a long-term job in quarter $S_i + t$, i.e.

$$Y_{iS_it} = \mathbb{1}(T_{i|S_i} \leq t + S_i). \tag{8}$$

The outcome variable for the treated when non-treated is denoted by $Y_{i\infty t}$ and it is such that

$$Y_{i\infty t} = \mathbb{1}(T_{i|\infty} \leq t + S_i). \tag{9}$$

Finally, in order to condition on not having made yet a transition to the endogenous censoring state at the evaluation quarter $S_i + t$, we define a censoring indicator C_{iS_it} as

$$C_{iS_it} = \begin{cases} 0 & \text{if } V_{i|S_i} \geq \min(T_{i|S_i}, t + S_i) \\ 1 & \text{otherwise.} \end{cases}$$

The estimand of interest is the conditional average treatment effect on the treated (CTT) (conditional on not being endogenously censored yet at the evaluation moment):

$$\Delta_t(s) = E\big[Y_{i\infty t} - Y_{iS_it} | D_{is} = 1, C_{iS_it} = 0\big], \text{ for } t = 1, \ldots, M_t. \tag{10}$$

The expectation is taken over the population. In our application $s = 7$ and $M_t = 8$. Note that, as $s \to \infty$ and without problems of endogenous censoring, the estimand in (10) would be the average treatment effect on the treated (ATT) on the probability of having already entered a long-term job t quarters after the treatment. If, in addition, we looked at $\Delta = \sum_{t=1}^{\infty} \Delta_t(\infty)$, we would have the ATT on the average duration between the treatment time and the entry in a long-term job.

Suppose that, for each treated individual, multiple realizations of the outcome variables when treated, Y_{iS_it}, and non-treated, $Y_{i\infty t}$, were observed. Then, we can identify the following conditional average individual treatment effect on the treated (CITT) for each i in the treated population not censored

difference in the post-treatment probability of having already got a long-term job is evaluated also for $s = 11$. Very similar results were obtained and are reported in appendix A-2, table A-8.

yet at the evaluation quarter:

$$\Delta_{it}(s) = E\big[Y_{i\infty t} - Y_{iS_it}|D_{is} = 1, C_{iS_it} = 0\big],\ \text{for } t = 1, \dots, M_t. \tag{11}$$

The expectation is, for each individual, over the multiple individual realizations of the outcome variables. Note that, for fixed t and s, the collection of the $\Delta_{it}(s)$'s provides the distribution of the CITT. In other words, it is the distribution of the difference in the probabilities of having already found a long-term job t quarters after the entry for the first time in a short-term job when short-term jobs are always rejected and when a short-term job was accepted.

Then, an estimand of interest for the CTT alternative to (10) is

$$\widetilde{\Delta}_t(s) = E\big[\Delta_{it}(s)\big],\ \text{for } t = 1, \dots, M_t, \tag{12}$$

where the expectation is taken over the treated population not endogenously censored yet at the evaluation quarter.

5.2.2 The Simulation Algorithm

In a nutshell, we simulate the population that is treated and then the outcome variable when treated and non treated. Moreover, for each treated individual, we can simulate several times the complete labour market career starting from treatment date when treated and non-treated. This means that we can obtain, for each of the treated, multiple realizations of the outcome variables $Y_{i\infty t}$ and Y_{iS_it} and we can draw, by looking at the simulated empirical counterpart of (11), the distribution of $\Delta_{it}(s)$. More in details, We perform simulations by proceeding in the following way:

(i) As explained at the beginning of section 5 we:

- draw a parameter vector according to its estimated distribution;
- draw a vector of individual unobserved effects;
- assign observed characteristics;
- simulate complete individual labour market histories up to the end of the time window.

(ii) We retain individuals who, in step (i):

- entered a short-term job (a job that lasted only one quarter) after an unemployment duration shorter than or equal to $s = 7$ quarters;
- were not endogenously censored yet t quarters after the occurrence of the short-term job.

The retained individuals are those satisfying the conditioning set in (10) or (11). Moreover, the retained population for $t > t'$ is always a subgroup of the retained population for t'.

(iii) For each retained individual in step (ii), we simulate 100 times labour market careers starting from the moment in which the treated got the first short-term job. Durations and destinations states are now simulated by transition lotteries at each quarter based on transition probabilities conditional on not being endogenously censored. The counterfactual is obtained by simulating, for the same retained population, labour market careers from the quarter of treatment by substituting the labour market status "unemployment" (still the post-school unemployment event) for "job" (the short-term job). Moreover, in the counterfactual simulations, we impose that the post-school unemployment spell can only be left for jobs strictly longer than one quarter.

(iv) On the basis of these 100 simulations per each individual, we estimate $\Delta_{it}(s)$ by taking the simulated empirical counterpart. At this point we have one simulation of the distribution of the CITT.

(v) We compute and store the mean (which is an estimate of $\widetilde{\Delta}_t(s)$ in (12)) and several selected percentiles of the CITT distribution obtained in step (iv).

(vi) We repeat steps (i)–(v) $R = 119$ independent times to get R independent distributions of the CITT.[17] The R realizations of the mean and percentiles of the CITT distribution are collected in R-dimensional vectors. We compute the means of these vectors. Their 95% confidence intervals are obtained by taking the $([.025R] + 1)/(R + 1)$th and the $([.975R] + 1)/(R + 1)$th element of the corresponding ascending order sorted vectors, where $[\alpha R]$ denotes the largest integer that is smaller than αR (Davidson and Mackinnon 2004, § 4.6).

5.2.3 Simulation Results

Table 6 reports means and selected percentiles of the CITTs distributions for $s = 7$ and $t = 1, 4, 8$. This means that the treated population, over which the displayed results were obtained, is made up of those who, in the simulation, entered a short term-job within the first 7 quarters of post-school unemployment and were not endogenously censored yet at the evaluation

[17] Note that the treated population not endogenously censored yet at the evaluation quarters can be different over the replications of steps (i)–(v).

quarter, i.e. after a post-treatment duration t.[18]

Rejections of short-term jobs during the post-school unemployment event, rather than acceptance of the first short-term job, significantly reduces the probability of having already entered a long-term job. The quarter after the short-term job, the difference in probability is already sizeable, significant, and equal to 6.7 and 4.3 percentage points, for men and women respectively. One and two years after the treatment the effects become even bigger: respectively, 14.2 and 19.3 percentages points for men and 13.1 and 13.6 for women.

Table 6: Simulated CITT Distributions for $s = 7$ and $t = 1, 4, 8$

	Distr of $\Delta_{i1}(7)$			Distr of $\Delta_{i4}(7)$			Distr $\Delta_{i8}(7)$		
Statistics	Mean	95% conf int		Mean	95% conf int		Mean	95% conf int	
					Men				
Mean	-.067	-.099	-.039	-.142	-.183	-.104	-.193	-.245	-.138
	(.171)			(.454)			(.682)		
Selected percentiles									
Minimum	-.638	-.770	-.510	-.886	-.960	-.800	-.972	-1.000	-.930
5th	-.383	-.452	-.327	-.652	-.734	-.570	-.750	-.830	-.657
10th	-.304	-.380	-.250	-.532	-.600	-.473	-.562	-.690	-.420
25th	-.174	-.210	-.140	-.299	-.390	-.220	-.248	-.310	-.190
50th	-.081	-.110	-.060	-.077	-.120	-.040	-.073	-.120	-.040
75th	.005	-.020	.090	.047	.010	.087	.016	-.010	.050
90th	.220	.180	.260	.133	.090	.170	.076	.040	.110
95th	.281	.240	.320	.180	.150	.220	.117	.080	.160
Maximum	.496	.410	.600	.355	.270	.490	.298	.210	.430
# obs$^{(a)}$		759.3			630.3			511.0	
					Women				
Mean	-.043	-.066	-.018	-.131	-.164	-.096	-.136	-.180	-.091
	(.149)			(.457)			(.673)		
Selected percentiles									
Minimum	-.644	-.750	-.530	-.890	-.970	-.790	-.959	-1.000	-.910
5th	-.304	-.350	-.260	-.639	-.700	-.580	-.735	-.810	-.654
10th	-.251	-.290	-.219	-.537	-.590	-.476	-.537	-.700	-.400
25th	-.171	-.200	-.140	-.271	-.360	-.210	-.217	-.278	-.158
50th	-.070	-.090	-.050	-.072	-.110	-.030	-.056	-.100	-.020
75th	.022	.000	.120	.055	.020	.090	.023	.000	.050
90th	.259	.220	.300	.145	.110	.180	.089	.060	.120
95th	.343	.300	.390	.197	.160	.240	.135	.100	.180
Maximum	.665	.490	.910	.414	.320	.550	.348	.250	.490
# obs$^{(a)}$		861.7			702.8			565.8	

Notes: In parentheses we report the average probability of having already entered a long-term job t quarters after the treatment for the treated, conditional on not being endogenously censored yet at the evaluation quarter. Formally, it is the mean over the R independent simulations of the empirical counterpart of $E\big[Y_{iS_it}|D_{i7}=1, C_{iS_it}=0\big]$.
$^{(a)}$ # obs indicates the average number of individuals satisfying the conditioning set in (11).

[18] The means and selected percentiles of the CITTs distributions for $s = 11$ and $t = 1, 4$ are instead reported in appendix A-2, table A-8. Very similar simulated distributions were obtained. Simulated CITTs distributions seem not to be biased by the selection rule based on s in order for an individual to be considered as treated.

The selected simulated percentiles of the CITTs distributions show that there is some heterogeneity in the treatment effect. Most of those who exited the post-school unemployment spell through a short-term contract would have suffered a lower a probability of finding a long-term job afterwards if they had rejected short-term contracts. The medians of each of the distributions are indeed significantly negative and around -7 percentage points. A clearer idea of the shape of the CITTs distributions is provided by figure 2. Note that the distribution of the change in the probability of having already entered a long-term job when short-term jobs are rejected varies with the post-treatment evaluation time. The later we evaluate the effect of rejections of short-term contracts, the more asymmetric the distribution becomes and a higher positive skewness is observed. The most important change occurs when we move t from 1 to 4 (8). In other words, when we evaluate the treatment effect four (eight) quarters after the rejection of the short-term contract, it is much easier to find individuals who would have heavily lost in terms of probability of finding a long-term job if they had rejected short-term contracts.

In order to understand the possible sources of heterogeneity in the treatment effect, we perform an OLS regression where the dependent variable is the simulated individual $\Delta_{i8}(7)$, stacked over the R replications of the simulation algorithm, on a set of characteristics fixed at the beginning of the observation period.[19] The OLS estimation results are reported in table 7. Even if almost all the coefficients are highly significant, their order of magnitude is small. The reduction in the probability of having already found a long-term job two years after the rejection of short-term contracts is less important for individual with at least a university degree and living in Flanders. Moreover, rejecting short-term jobs seems to particularly damage individuals who live in areas where the unemployment rate is higher.

Summarizing, short-term jobs are found to be springboards to long-term jobs. As a matter of fact, rejecting short-term jobs as a channel out of the post-school unemployment spell results, in average, in significantly lower probabilities of finding stabler positions in the short- and medium-term. This evidence apparently contrasts with the model estimates suggesting positive correlation between unemployment duration and subsequent job stability. However, by way of simulations, labour market trajectories are taken into account over a four years time span; therefore the stepping stone effect is the result of the interaction of direct and indirect effects that makes short-term jobs more beneficial, in terms of career stability, than further quarters spent

[19] OLS estimation results of $\Delta_{i1}(7)$ and $\Delta_{i4}(7)$ on individual characteristics are available upon request from the authors.

Figure 2: Simulated CITT Distributions for $s = 7$ and $t = 1, 4, 8$

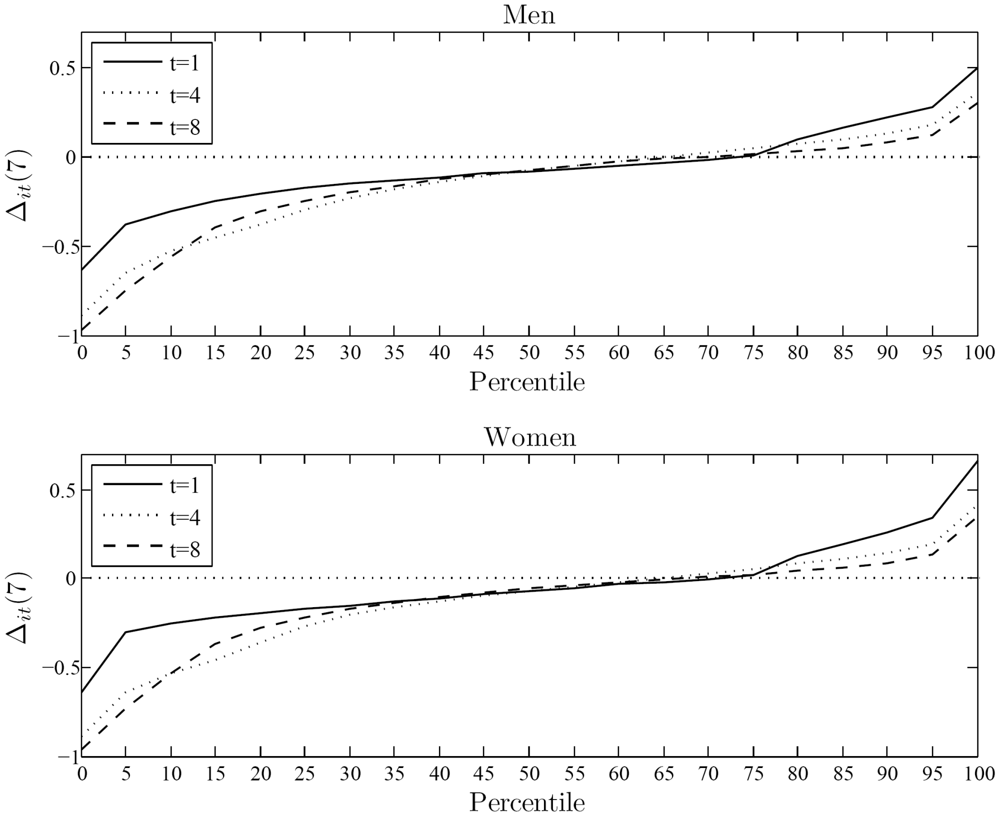


Table 7: OLS Estimation Results of $\Delta_{i8}(7)$ on Individual Characteristics

Dependent variable: $\Delta_{i8}(7)$	Men		Women	
Variable	Coeff	S.E.	Coeff	S.E.
Nationality - Reference: Belgian				
Non Belgian UE	-.005	.005	.002	.005
Non Belgian non UE	.018***	.005	-.035***	.006
Education - Reference: Higher secondary school				
Primary education	.022***	.004	.013**	.006
Lower secondary education	-.002	.003	-.012***	.003
University or more	.054***	.003	.069***	.002
Other	.011	.013	.051***	.011
Unknown	.169***	.003	.109***	.003
Region of residence - Reference: Wallonia				
Flanders	.041***	.005	.037***	.004
Brussels	.002	.004	-.004	.004
Household position - Reference: Cohabitant				
Head of household	-.025***	.005	-.030***	.006
Single	-.016***	.004	-.008**	.004
Pre-treatment unemployment duration	.002***	.001	-.007***	.001
Local unemployment rate	-.055*	.028	-.070***	.019
Individual heterogeneity type - Reference: Type 1				
Type 2	.104***	.004	.052***	.003
Type 3	.055***	.003	.138***	.003
Type 4	.189***	.004*	.094***	.002
Type 5	–	–	-.112***	.016
Constant	-.238***	.004	-.181***	.007
Observations	60,809		67,205	
R^2	.077		.067	

Notes: * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. The reference individual is Belgian, cohabitant, has higher secondary school degree, lives in Wallonia and in a subregion with average unemployment rate, has individual heterogeneity of type 1 and an average pre-treatment duration of unemployment.

in unemployment looking for a better job. According to the estimated lagged duration and occurrence dependences, the main sources of this finding are:

- Firstly, negative unemployment duration dependence was found and therefore, when a short-term job is rejected for further periods of unemployment, the probability of finding any other job becomes lower and lower over time.
- Secondly, it was found that a job event *per se* raises the subsequent unemployment exit rate. Hence, the rejection of short-term jobs implies also rejecting the increase in subsequent unemployment exit rates in case of displacement at the end of the contract.
- Finally, if the worker were able to move directly to another job at the end of the short-term contract, the new job would be more likely to be longer-lived than a similar job entered from unemployment.

Hence, policy interventions aimed for speeding up the job-matching process for Belgian long-term unemployed school-leavers may increase their labour market integration, employability, and career stability, even if this would be done through the spread of short-lived jobs. As a matter of fact, it is better, in terms of subsequent career stability, to enter even a short-term job than waiting longer in unemployment for a longer lasting job.

6 Conclusions

This study deepens the understanding of the mechanisms driving the labour market dynamics of the disadvantaged Belgian youth and highlights the strategies for their labour market reintegration, employability, and career stability.

The analysis was performed using a Belgian administrative dataset on young school-leavers without any labour market experience and entitled for the first time to unemployment benefits in 1998 after 9 months of job search. Their labour market transitions are followed on a quarterly basis until the end of 2001.

In a first step, a flexible multi-spell multi-state MPH model in a competing risks framework was estimated to understand the effect of previous labour market outcomes on the subsequent labour market performance. The model estimation results showed that:

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

ii) Rather, job experiences as such generate a large positive effect (75.1% for women and 37.6% for men) on the exit rate from subsequent unemployment spells. This means that long-term unemployed school-leavers can reduce their unemployment experience drastically by accepting any job, be it short or long.

iii) Conditional on job leaving, short-term jobs lead to shorter subsequent jobs but do not affect the re-employment rate if the job was left for unemployment. The first effect is large: decreasing the tenure in the previous job by one quarter increases the current job-to-unemployment transition intensity by 13.5% for men and 6.5% for women. In addition, for women it increases the job-to-job transitions by 4.3%. This provides evidence of a tendency to cycle between short-term jobs.

iv) Lagged unemployment duration enhances job stability of subsequent jobs. This is evidence that workers may improve the job match quality by postponing the exit from unemployment(Marimon and Zilibotti 1999) and that it may be worthwhile, *ceteris paribus*, to reject short-term jobs to increase the likelihood of a long-lasting employment relation.

On the basis of these results it is difficult to conclude whether short-term jobs are springboards to long-term jobs, since there are some effects that support the hypothesis (cf. e.g. ii)) and others that negate it (cf. e.g. iii) and iv)). That is why we simulated, in a second step, the model in order find out which effects were dominant. On this basis we can conclude that rejecting short-term jobs at the beginning of the labour market career reduces, within two years, the probability of entering a long-term job by 19.3 percentage points for men and 13.6 for women. On the other hand, the simulated distribution of the individual effect showed that about 25% of the treated would have increased their chances of being hired in a long-term job by rejecting these short-term jobs. However, we were not able to identify, on the basis of observed individual characteristics, a subpopulation that would have increased their likelihood of long-term employment by rejecting short-term jobs. Consequently, although the stepping stone effect of short-term jobs is less important for certain subpopulations (for those who live in Flanders or in a district with a lower unemployment rate and for those who are higher educated), it is always significantly positive.

Appendix

A-1 Deriving the Likelihood Function

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

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

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

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

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

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

where $\mathscr{J} = \mathscr{E}$ if $j = e$ and $\mathscr{J} = \mathscr{U}$ if $j = u$. We assume now that the transition intensities are constant within two consecutive quarters since we do not have information on what happens within each interval. Under this assumption we can specify the discrete time process as a continuous time model and the hazard functions can be taken out of the integrals, yielding

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

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

$$\begin{aligned} \Pr \quad & (t_s - 1 \leq T_j < t_s, D_{jk} = 1 | T_j \geq t_s - 1) \\ = \quad & \frac{\int_{t_s-1}^{t_s} \theta_{jk}^s(\tau) \exp\Big\{ - \int_0^\tau \sum_{(j,k)\in\mathscr{J}} \theta_{jk}^s(r) dr \Big\} d\tau}{\exp\Big\{ - \int_0^{t_s-1} \sum_{(j,k)\in\mathscr{J}} \theta_{jk}^s(r) dr \Big\}} \end{aligned} \tag{A-3}$$

and exploiting again the assumption that the transition intensities are constant within two consecutive quarters, equation (A-3) can be rewritten, following Cockx (1997), as

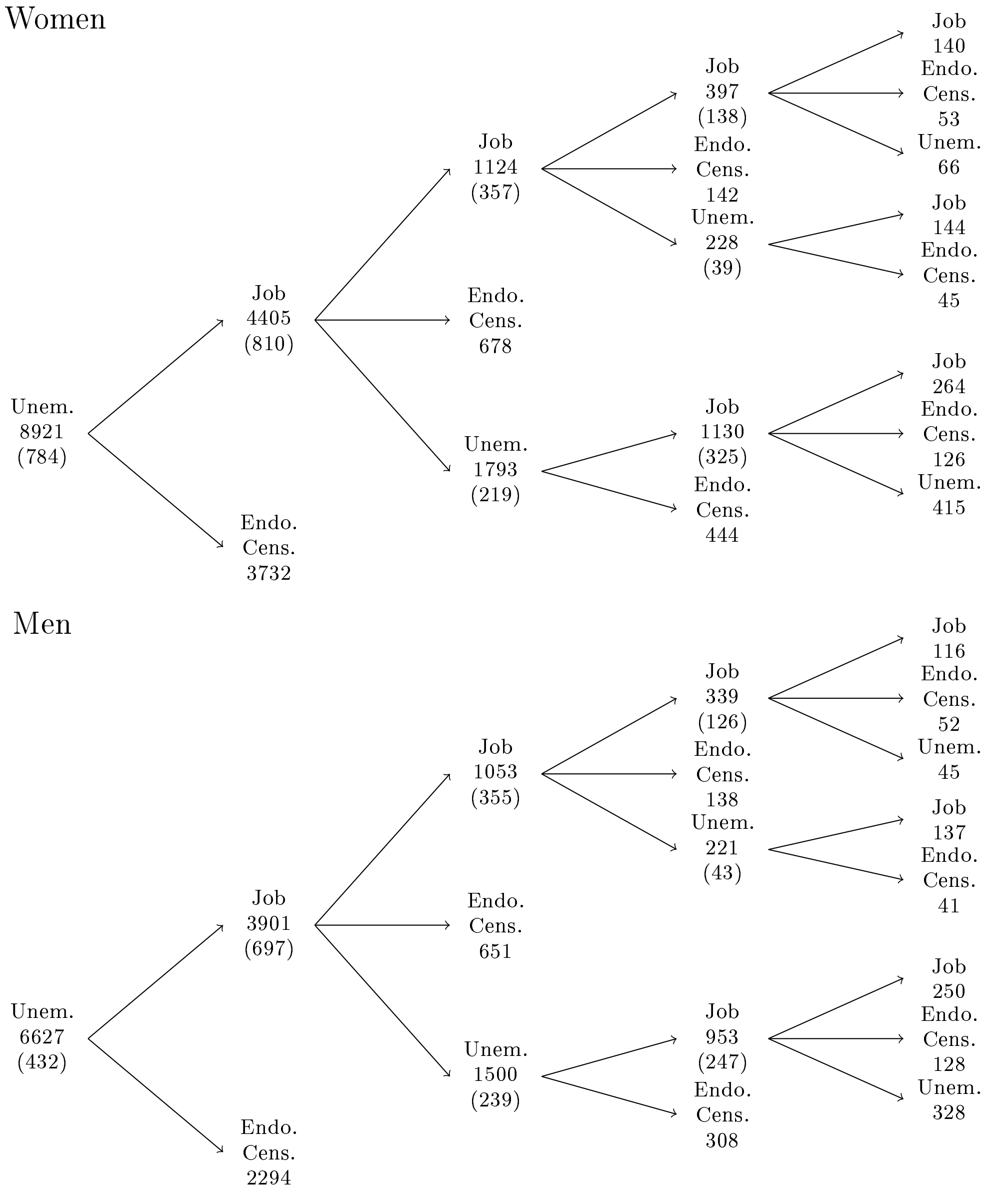
$$\Big[1 - \exp\Big\{ - \sum_{(j,k)\in\mathscr{J}} \theta_{jk}^s(t_s) \Big\}\Big] \times \frac{\theta_{jk}^s(t_s)}{\sum_{(b,c)\in\mathscr{J}} \theta_{bc}^s(t_s)}. \tag{A-4}$$

Multiplying (A-2) by (A-4) and reintroducing the set of observed and observed characteristics yield equation (3), which is the contribution to the likelihood function of a complete spell s for $j \in \{u, e\}$.

A-2 Further Estimation Results

This appendix displays descriptive statistics and estimation results not presented in the main text for the sake of brevity. Table A-1 contains means and standard deviations of the time-varying variables at the beginning of the first five labour market spells. Tables A-2–A-6 comprise estimated parameters of the benchmark model not reported in the main text for the sake of brevity. Table A-7 displays estimation results of lagged duration and occurrence dependences of the model where the initial conditions problem is approximated following Heckman (1981). Finally, table A-8 reports means and selected percentiles of the CITTs distributions for $s = 11$ and $t = 1, 4$.

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



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

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

Spell	2nd		3rd		4th		5th	
Variable	Men	Women	Men	Women	Men	Women	Men	Women
Age	21.5(2.1)	21.6(2.1)	22.1(2.1)	22.2(2.1)	22.5(2.1)	22.7(2.2)	22.7(2.4)	22.9(2.4)
Monthly unemployment benefits (in €)	–	–	426.1(193.5)	389.9(175.5)	498.3(229.1)	437.2(200.1)	484.5(215.5)	423.3(195.1)
Declining benefits	–	–	.138(.35)	.098(.30)	.317(.47)	.232(.42)	.209(.41)	.175(.38)
Quarter of entry in the spell								
January-February-March	.233(.42)	.250(.43)	.286(.45)	.256(.44)	.266(.44)	.269(.44)	.234(.42)	.259(.44)
April-May-June	.158(.36)	.157(.36)	.264(.44)	.270(.44)	.246(.43)	.227(.42)	.237(.43)	.244(.43)
July-August-September	.303(.46)	.301(.46)	.172(.38)	.165(.37)	.279(.45)	.280(.45)	.221(.41)	.220(.41)
October-November-December	.306(.46)	.292(.45)	.279(.45)	.310(.46)	.210(.41)	.223(.42)	.308(.46)	.276(.45)
Household position								
Head of Household	.061(.24)	.059(.24)	.088(.28)	.073(.26)	.087(.28)	.058(.23)	.107(.31)	.064(.25)
Single	.121(.33)	.097(.30)	.170(.38)	.124(.33)	.167(.37)	.142(.35)	.187(.39)	.135(.34)
Cohabitant	.818(.39)	.844(.36)	.742(.44)	.802(.40)	.746(.44)	.800(.40)	.706(.46)	.801(.40)
Firm size								
$[1, 20)$ employees	.272(.45)	.254(.44)	.280(.45)	.272(.45)	.241(.43)	.236(.42)	.237(.43)	.265(.44)
$[20, 50)$ employees	.063(.24)	.071(.26)	.101(.30)	.096(.29)	.072(.26)	.090(.29)	.105(.31)	.089(.29)
$[50, 100)$ employees	.044(.21)	.044(.20)	.057(.23)	.062(.24)	.044(.21)	.047(.21)	.062(.24)	.051(.22)
$[100, 500)$ employees	.135(.34)	.142(.35)	.148(.36)	.138(.34)	.142(.35)	.136(.34)	.167(.37)	.113(.32)
500 or more employees	.486(.50)	.489(.50)	.414(.49)	.434(.50)	.500(.50)	.492(.50)	.433(.50)	.488(.50)
Sector								
Agriculture	.029(.17)	.018(.13)	.013(.11)	.006(.08)	.018(.13)	.009(.01)	.014(.12)	.011(.10)
Industry & Mining	.086(.28)	.039(.19)	.157(.36)	.070(.26)	.095(.29)	.046(.21)	.163(.37)	.100(.30)
Building & Energy	.082(.27)	.011(.10)	.103(.30)	.005(.07)	.064(.25)	.009(.09)	.084(.28)	.007(.09)
Wholesale & Retail trade	.164(.37)	.183(.39)	.192(.39)	.225(.42)	.190(.39)	.186(.39)	.185(.39)	.214(.41)
Credit & Insurance	.014(.12)	.017(.13)	.026(.16)	.037(.19)	.013(.11)	.020(.14)	.024(.15)	.018(.13)
Business services	.420(.49)	.343(.47)	.356(.48)	.313(.46)	.418(.49)	.367(.48)	.380(.49)	.330(.47)
Other services & Public administration	.205(.40)	.390(.49)	.154(.36)	.341(.47)	.201(.40)	.364(.48)	.147(.35)	.318(.40)
Unemployment rate	.174(.07)	.251(.09)	.168(.07)	.236(.10)	.163(.07)	.227(.10)	.216(.09)	.160(.07)

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

Table A-2: Estimation Results of the Baseline Hazards by Gender

Transition	(u,e)		(u,a)			(e,e)		(e,u)		(e,a)	
Quarters	Coeff.	S.E.	Coeff.	S.E.	Quarters	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
					Men						
2nd	-.206***	.076	-.074	.137	2nd	-.110	.068	-.298***	.062	-.236**	.092
3rd	-.254***	.092	.134	.152	3rd	-.372***	.083	-.766***	.093	-.245**	.112
4th	-.428***	.093	-.138	.124	4th	-.185***	.092	-.302***	.093	-.106	.128
5th	-.581***	.098	.265**	.122	5-6th	-.606***	.097	-1.386***	.130	-.559***	.139
6th	-.715***	.103	.267**	.127	7-9th	-.810***	.112	-1.057***	.130	-.661***	.156
7th	-.887***	.112	.106	.134	10-15th	-1.025***	.157	-1.160***	.192	-.735***	.211
8-9th	-.639***	.110	-.087	.136							
10-12th	-.753***	.120	-.043	.143							
13-19th	-.861***	.134	.036	.156							
					Women						
2nd	-.196***	.070	.202*	.111	2nd	-.185***	.061	-.476***	.057	-.067	.100
3rd	-.101	.089	.441***	.122	3rd	-.580***	.082	-.932***	.078	.221*	.120
4th	-.373***	.093	-.021	.102	4th	-.368***	.085	-.439***	.078	.160	.147
5th	-.519***	.099	.396***	.101	5-6th	-.729***	.093	-1.489***	.105	-.026	.164
6th	-.504***	.105	.285***	.107	7-9th	-1.002***	.107	-1.543***	.118	-.061	.187
7th	-.644***	.112	.222**	.112	10-15th	-.987***	.137	-2.291***	.212	.097	.229
8-9th	-.585***	.114	.147	.114							
10-12th	-.655***	.122	.136	.120							
13-19th	-.995***	.134	.138	.130							

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

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

Transition	(u,e)		(e,e)		(e,u)	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Time-invariant covariates $\mathbf{x}_{jk}^0$						
Nationality - Reference: Belgian						
Non-Belgian EU	-.037	.083	.003	.122	.121	.110
Non EU	-.110	.079	.089	.124	.264**	.114
Education - Reference: Higher secondary						
Primary school	-.711***	.068	-.049	.106	.701***	.114
Lower secondary	-.503***	.052	-.048	.070	.477***	.083
Higher education	.448***	.085	.209**	.087	-.395***	.115
Other	-.666***	.194	-.211	.343	.524**	.246
Unknown	1.381***	.133	.138	.287	-3.363***	.338
Region of residence - Reference: Wallonia						
Flanders	.312***	.083	.343***	.098	-.017	.120
Brussels	.073	.061	-.172*	.092	-.071	.083
Time-variant spell-specific variables $\mathbf{x}_{jk}^1$						
Age	-.024**	.012	-.052***	.016	-.016	.017
Household position - Reference: Cohabitant						
Head of household	-.082	.149	-.021	.102	.339***	.099
Single	-.140**	.061	.104	.069	.400***	.074
Quarter of entry in the spell - Reference: April-May-June						
January-February-March	-.055	.059	.028	.071	.355***	.076
July-August-September	-.118**	.054	.014	.067	.234***	.075
October-November-December	-.189***	.058	-.050	.071	.215***	.076
Firm size - Reference: 500 or more employees						
$[1, 20)$ employees	–	–	-.200***	.063	-.335***	.066
$[20, 50)$ employees	–	–	-.217**	.094	-.268***	.100
$[50, 100)$ employees	–	–	-.268**	.119	-.218*	.122
$[100, 500)$ employees	–	–	-.206***	.072	-.241***	.076
Sector - Reference: Business services						
Agriculture	–	–	-.624***	.182	.400***	.141
Industry & Mining	–	–	-1.152***	.089	-.812***	.094
Building & Energy	–	–	-.888***	.092	-.994***	.110
Wholesale & Retail trade	–	–	-1.119***	.076	-.923***	.077
Credit & Insurance	–	–	-1.048***	.194	-1.177***	.272
Other services & Pub. Adm.	–	–	-1.430***	.078	-.912***	.076
Log unemployment benefits	-.467***	.131	–	–	–	–
Declining benefits	.246	.362	–	–	–	–
Time-variant variables $\mathbf{x}_{jk}^2$						
Local unemployment rate	-1.440***	.407	.238	.572	1.323**	.628
Quarters away of a decline in the unemployment benefit amount						
UI 4	-.075	.371	–	–	–	–
UI 3	.127	.191	–	–	–	–
UI 2	-.294	.278	–	–	–	–
UI 1	.434	.360	–	–	–	–
Individual heterogeneity distribution – $M = 4$						
Support points						
$\ln v_{jk1}$	.183	.225	-1.146***	.224	-2.639***	.280
$\ln v_{jk2}$	-.797***	.262	-1.477***	.353	-.504*	.273
$\ln v_{jk3}$	.301	.215	-.504**	.198	-1.299***	.237
$\ln v_{jk4}$	-.258	.260	.874	.558	.925*	.482
Probability masses (logistic transform)				Resulting probabilities		
λ_1	5.563***	.766		p_1	.372	
λ_2	3.670***	.734		p_2	.056	
λ_3	5.988***	.706		p_3	.570	
λ_4	.000	–		p_4	.001	

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

Table A-4: Continuing Table A-3

Transition	(u,a)		(e,a)	
Variable	Coeff.	S.E.	Coeff.	S.E.
Time-invariant covariates $\mathbf{x}_{jk}^0$				
Nationality - Reference: Belgian				
Non-Belgian EU	-.090	.094	-.069	.147
Non EU	-.144	.093	.126	.137
Education - Reference: Higher secondary				
Primary school	-.420***	.080	.685***	.123
Lower secondary	-.311***	.062	.456***	.092
Higher education	.310***	.085	-.229*	.127
Other	-.416*	.214	.302	.386
Unknown	.709***	.171	-.911***	.270
Region of residence - Reference: Wallonia				
Flanders	.287***	.089	.047	.130
Brussels	.082	.067	.146	.102
Time-variant spell-specific variables $\mathbf{x}_{jk}^1$				
Age	-.029**	.013	.006	.020
Household position - Reference: Cohabitant				
Head of household	.055	.186	.145	.133
Single	.097	.072	.176*	.096
Quarter of entry in the spell - Reference: April-May-June				
January-February-March	.008	.084	.144	.096
July-August-September	-.134*	.071	.101	.094
October-November-December	.109	.076	.184**	.093
Firm size - Reference: 500 or more employees				
$[1,20)$ employees	–	–	-.084	.081
$[20,50)$ employees	–	–	-.285**	.135
$[50,100)$ employees	–	–	-.189	.147
$[100,500)$ employees	–	–	-.250**	.101
Sector - Reference: Business services				
Agriculture	–	–	-.111	.211
Industry & Mining	–	–	-.707***	.120
Building & Energy	–	–	-.773***	.132
Wholesale & Retail trade	–	–	-.940***	.102
Credit & Insurance	–	–	-.711**	.276
Other services & Pub. Adm.	–	–	-.755***	.095
Log unemployment benefits	-.404**	.185	–	–
Time-variant variables $\mathbf{x}_{jk}^2$				
Local unemployment rate	-2.247***	.470	-1.572**	.756
Lagged duration and occurrence dependence				
Lagged unemployment duration	–	–	.021*	.012
Previous state: unemployment	–	–	.120	.129
Lagged job tenure	.053	.034	.033	.033
Individual heterogeneity distribution – $M = 4$				
Support points				
$\ln v_{jk1}$	-1.263***	.357*	-2.888***	.322
$\ln v_{jk2}$	-1.721***	.303	-1.993***	.332
$\ln v_{jk3}$	-1.157***	.304	-2.163***	.244
$\ln v_{jk4}$	$-\infty$	–	$-\infty$	–

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

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

Transition	(u,e)		(e,e)		(e,u)	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Time-invariant covariates $\mathbf{x}^0_{jk}$						
Nationality - Reference: Belgian						
Non-Belgian EU	-.063	.072	-.102	.129	-.003	.113
Non EU	-.757***	.078	-.375***	.136	.154	.110
Education - Reference: Higher secondary						
Primary school	-.969***	.083	-.166	.143	.521***	.113
Lower secondary	-.727***	.054	-.185**	.089	.329***	.069
Higher education	.774***	.059	.192***	.073	-.236***	.077
Other	-.677***	.188	-.031	.429	.823***	.253
Unknown	1.089***	.130	-.288**	.118	-2.021***	.247
Region of residence - Reference: Wallonia						
Flanders	.451***	.065	.248***	.094	-.096	.086
Brussels	.085	.061	.177**	.085	-.173**	.085
Time-variant spell-specific variables $\mathbf{x}^1_{jk}$						
Age	-.006	.010	.005	.015	-.037**	.016
Household position - Reference: Cohabitant						
Head of household	-1.358***	.202	-.213*	.110	.224***	.087
Single	-.235***	.072	-.048	.081	-.005	.072
Quarter of entry in the spell - Reference: April-May-June						
January-February-March	-.217***	.062	.077	.067	.163**	.067
July-August-September	-.073	.052	.055	.066	.204***	.065
October-November-December	-.215***	.054	-.006	.067	-.004	.068
Firm size - Reference: 500 or more employees						
$[1,20)$ employees	–	–	-.362***	.059	-.422***	.056
$[20,50)$ employees	–	–	-.243***	.082	-.428***	.086
$[50,100)$ employees	–	–	-.177	.109	-.195*	.106
$[100,500)$ employees	–	–	-.083	.070	-.274***	.068
Sector - Reference: Business services						
Agriculture	–	–	.075	.224	.881***	.134
Industry & Mining	–	–	-1.321***	.120	-.528***	.111
Building & Energy	–	–	-1.079***	.255	-.764***	.278
Wholesale & Retail trade	–	–	-1.062***	.069	-.646***	.067
Credit & Insurance	–	–	-1.143***	.161	-1.408***	.233
Other services & Pub. Adm.	–	–	-1.238***	.059	-.688***	.057
Log unemployment benefits	.519**	.207	–	–	–	–
Declining benefits	.009	.369	–	–	–	–
Time-variant variables $\mathbf{x}^2_{jk}$						
Local unemployment rate	-1.423***	.281	-1.233***	.434	.642*	.371
Quarters away of a decline in the unemployment benefit amount						
UI 4	-.475	.359	–	–	–	–
UI 3	-.223	.211	–	–	–	–
UI 2	-.723**	.353	–	–	–	–
UI 1	1.093***	.418	–	–	–	–
Individual heterogeneity distribution – $M=5$						
Support points						
$\ln v_{jk1}$	-1.477***	.300	-1.068***	.228	-1.361***	.214
$\ln v_{jk2}$	-2.387***	.326	-.673***	.241	.005	.244
$\ln v_{jk3}$	-1.190***	.356	$-\infty$	–	.005	.271
$\ln v_{jk4}$	-.632**	.300	-.045	.221	-1.060***	.223
$\ln v_{jk5}$	-1.817***	.395	-.468	.317	$-\infty$	–
Probability masses (logistic transform)				Resulting probabilities		
λ_1	2.404***	.449		p_1	.507	
λ_2	1.549***	.463		p_2	.216	
λ_3	-.135	.694		p_3	.040	
λ_4	1.431**	.580		p_4	.191	
λ_5	.000	–		p_5	.046	

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

Table A-6: Continuing Table A-5

Transition	(u,a)		(e,a)	
Variable	Coeff.	S.E.	Coeff.	S.E.
Time-invariant covariates $\mathbf{x}^0_{jk}$				
Nationality - Reference: Belgian				
Non-Belgian EU	-.191***	.072	-.031	.169
Non EU	-.290***	.069	-.490**	.223
Education - Reference: Higher secondary				
Primary school	-.184***	.065	.687***	.189
Lower secondary	.046	.044	.269**	.127
Higher education	.359***	.060	-.281**	.126
Other	-.422**	.190	.785*	.410
Unknown	.723***	.131	-1.436***	.306
Region of residence - Reference: Wallonia				
Flanders	.247***	.062	.130	.136
Brussels	.068	.055	.099	.131
Time-variant spell-specific variables $\mathbf{x}^1_{jk}$				
Age	-.022**	.010	.035	.024
Household position - Reference: Cohabitant				
Head of household	.033	.164	.076	.172
Single	.043	.064	.325***	.113
Quarter of entry in the spell - Reference: April-May-June				
January-February-March	.039	.068	.111	.111
July-August-September	-.167***	.057	.215**	.108
October-November-December	.133**	.060	.010	.110
Firm size - Reference: 500 or more employees				
$[1,20)$ employees	–	–	-.207**	.093
$[20,50)$ employees	–	–	-.476***	.148
$[50,100)$ employees	–	–	-.036	.171
$[100,500)$ employees	–	–	-.211*	.115
Sector - Reference: Business services				
Agriculture	–	–	-.200	.472
Industry & Mining	–	–	-.774***	.185
Building & Energy	–	–	-1.253***	.443
Wholesale & Retail trade	–	–	-.541***	.112
Credit & Insurance	–	–	-.987***	.301
Other services & Pub. Adm.	–	–	-.534***	.100
Log unemployment benefits	-.217	.165	–	–
Time-variant variables $\mathbf{x}^2_{jk}$				
Local unemployment rate	-1.164***	.273	-.863	.625
Lagged duration and occurrence dependence				
Lagged unemployment duration	–	–	-.023	.021
Previous state: unemployment	–	–	.214	.186
Lagged job tenure	.051	.025	.027	.035
Individual heterogeneity distribution – $M=5$				
Support points				
$\ln v_{jk1}$	-1.835***	.280	-3.302***	.334
$\ln v_{jk2}$	-1.904***	.270	-3.140***	.507
$\ln v_{jk3}$	-2.118***	.604	-1.557***	.447
$\ln v_{jk4}$	-1.445***	.360	-2.874***	.349
$\ln v_{jk5}$	-2.539***	.787	-.543	.352

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

Table A-7: Lagged Duration Dependence Estimation Results (Heckman's (1981) Correction of Initial Conditions)

Transition	(u, e)		(e, e)		(e, u)	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
			Men			
Lagged unemployment duration	–	–	-.023	.015	-.041***	.013
Previous state: unemployment	–	–	-.139	.104	.196	.135
Lagged job tenure	-.018	.024	-.036	.023	-.137***	.037
# of observations	6,627		# of spells		16,447	
# of parameters	232		Log-likelihood		-41,146.7	
Vuong's LR test of nonnested models:[a]			T_{LR}=1.025		p-value=0.305	
			Women			
Lagged unemployment duration	–	–	-.048***	.015	-.042***	.012
Previous state: unemployment	–	–	-.190**	.086	.334***	.115
Lagged job tenure	-.045**	.020	-.059***	.019	-.058**	.028
# of observations	8,921		# of spells		20,275	
# of parameters	239		Log-likelihood		-51,186.4	
Vuong's LR test of nonnested models:[a]			T_{LR}=-1.477		p-value=0.140	

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

[a] Vuong's (1989) test of strictly nonnested models is used here to compare the benchmark model to Heckman's (1981) correction of initial conditions. The test was modified to permit AIC log-likelihood penalties.

Table A-8: Estimated CITT Distributions for $s = 11$ and $t = 1, 4$

	Distr of $\Delta_{i1}(11)$			Distr of $\Delta_{i4}(11)$		
Statistics	Mean	95% conf int		Mean	95% conf int	
			Men			
Mean	-.068	-.093	-.044	-.144	-.178	-.104
Selected percentiles						
Minimum	-.644	-.770	-.530	-.894	-.960	-.830
5th	-.376	-.440	-.320	-.647	-.720	-.590
10th	-.296	-.368	-.250	-.526	-.580	-.470
25th	-.170	-.200	-.140	-.301	-.390	-.250
50th	-.078	-.100	-.060	-.084	-.125	-.050
75th	-.006	-.020	.000	.045	.010	.080
90th	.216	.170	.250	.136	.100	.180
95th	.281	.240	.318	.186	.150	.230
Maximum	.507	.440	.600	.381	.300	.500
# obs[(a)]		1099.9			911.9	
			Women			
Mean	-.046	-.064	-.024	-.135	-.169	-.101
Selected percentiles						
Minimum	-.653	-.800	-.540	-.903	-.970	-.810
5th	-.299	-.350	-.260	-.633	-.685	-.581
10th	-.245	-.280	-.210	-.536	-.589	-.490
25th	-.165	-.190	-.130	-.284	-.360	-.230
50th	-.067	-.090	-.050	-.082	-.110	-.050
75th	-.000	-.010	.000	.053	.020	.090
90th	.252	.210	.294	.150	.120	.190
95th	.344	.302	.385	.205	.170	.250
Maximum	.675	.500	.910	.446	.350	.560
# obs[(a)]		1237.5			1004.5	

[(a)] # obs indicates the average number of individuals satisfying the conditioning set in (11).

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