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Exits from temporary jobs in Europe: A competing risks analysis

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Abstract

We study transitions out of temporary jobs using the waves 1994–1999 of the European Community Household Panel applying a discrete time duration model. Specifically, we use a multinomial logit model distinguishing between exits into permanent employment and non-employment. Two different specifications are presented, one does not account for unobserved heterogeneity while the other does. Unobserved heterogeneity is assumed to follow a discrete distribution. The competing risks model is estimated jointly for all EU Member States. The duration dependence parameters suggest that in general for EU as a whole, very short contracts provide higher chances of labour market exclusion especially for men. We discuss potential implications of our findings.

JEL classification: J24; C41; C33; C35; J6
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1. Introduction

In this study, we are concerned with the fates of individuals who hold temporary jobs in the European Union. Temporary jobs have been used to try to cope with high unemployment

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rates, the intention being that a temporary job could potentially provide a path of entry or reentry into the core group of the labour market. Non-standard employment patterns (represented by part-time, agency work, temporary contracts or other flexible arrangements) may offer a solution to a number of workers, but are often associated with poorer labour conditions (wage, working time, job security, working time, etc.) and thus likely also with lower job quality.[2] The risk of experiencing precarious career paths can therefore be higher for people in such flexible working arrangements. Ultimately, it may be that individuals in these jobs are at risk of exclusion from the labour market.

It is also important to consider the motives of employers offering such arrangements. From the employers' perspective, temporary working arrangements may provide a way to cope with demand fluctuations in an environment where the 'ordinary' labour market is characterized by permanent job types with fairly high firing costs (see Bentolila and Bertola, 1990; Bentolila and Saint-Paul, 1994; Booth, 1997). Temporary employment may lower firms' adjustment costs, but may worsen workers' living conditions. Flexibility can be a choice on the firms' side, but often it is accompanied by precariousness and instability on the employees' side.

The crucial question, thus, is whether, on average, temporary jobs help workers back into the labour market, or if they rather have the opposite effect. Although a growing number of analyses are performed, it is still unclear if these flexible jobs are associated with good performances in the subsequent career both in terms of wages and of working opportunities (see e.g. for Spain, Dolado et al., 2002; Petrongolo and Güell, 2001; and for the UK, Booth et al., 2001, 2002a,b).[3] Specifically, it is not clear whether they are "stepping stones" or "deadend" jobs.

Our paper analyses transitions out of temporary jobs in a discrete duration model framework. The analysis provides evidence about factors correlated with "good" outcomes (leading therefore to inclusion-permanent employment) or with "bad" outcomes (leading to exclusion-non-participation). We distinguish therefore two destination states (permanent employment and non-participation) that can be entered when leaving a temporary job. For this purpose, we use the waves 1994–1999 of the European Community Household Panel (ECHP). The analyses are performed separately for men and women, and jointly for all the EU Member countries.[4]

It should be noted at the outset that the analysis carried out in this study is descriptive; we are not estimating the effect of having a temporary job relative to some counterfactual situation (as the counterfactual situation is not easily specified). Our aim is to describe subsequent labour market outcomes of those holding temporary contracts, and to investigate factors associated with 'good' and 'bad' outcomes.

Our sample consists of individuals starting a temporary job during the 1994–1999 waves of the ECHP. The duration of interest is temporary job duration and the destinations we focus on are: (1) permanent job; and (2) non-employment. We adopt therefore a

[2] For a definition of job quality see European Commission (2002). See also Salverda et al. (2001).

[3] See also the volume 112 of the Economic Journal (2002) for a collection of articles on temporary works in Spain, UK, France and Sweden.

[4] We have also performed the estimations by country for a set of Member countries. For the sake of exposition, these results are not reported but are available upon request from the authors.

competing risks duration model. Given the discrete nature of the data we use methods for discrete duration data (see Heckman, 1981). Specifically, we use a multinomial logit model (MLM), which is one way of estimating a competing risks duration model in discrete time. We estimate the transitions into both destinations simultaneously, allowing each of them to have different time patterns and to be differently affected by covariates. Two different specifications are presented, the first does not account for potential unobserved heterogeneity while the second does. Unobserved heterogeneity is assumed to follow a discrete distribution with two points of support (see Heckman and Singer, 1984; Lindsay, 1995). This specification avoids the IIA (Independence of Irrelevant Alternatives) assumption implicit in the standard MLM.

Some interesting results are revealed by the analysis. First, although some factors differently affect men's and women's transitions into permanent employment and non-employment, others affect them in the same way by reducing the probability of job stability and symmetrically by increasing that of job instability. These are: the experience of nonemployment before entering the temporary work arrangement, the labour market conditions (i.e. the unemployment rate), being occupied in some elementary tasks, and having a temporary job in the public sector. Second, older people, less experienced workers, individuals earning very low wages and women with young children are at higher risk of exclusion. Third, unobservables play an important role in determining workers outcomes especially for women. Fourth, the duration dependence parameters suggest that very short contracts are associated with higher risks of labour market exclusion, especially for men.

The paper is organized as follows. Econometric models applied are illustrated in the next section. We describe the data and variables used in Section 3. The results are discussed in Section 4. Section 5 draws some conclusions.

2. Modelling strategy

The typical framework to analyse labour market transitions is the job-search approach (see Burdett, 1978; Burdett and Mortensen, 1980; Lancaster, 1990; Devine and Kiefer, 1991). The duration of a labour market spell is modelled by specifying the conditional probability of leaving that spell; the hazard rate. The hazard rate out of a job can be seen as the sum of two conditional probabilities: the probability of a worker receiving an acceptable alternative job offer and the probability of a worker being (permanently) laid off.

In general, workers will leave jobs if the expected utility flows available outside the job (plus any costs incurred by leaving) exceed those in the job. Firms will terminate a job if the profits from doing so, less firing costs, exceed the profits of maintaining the job. We might expect the hazard rate from jobs to fluctuate non-monotonically with duration. Job separation rates may increase initially, as workers and firms learn about the quality of the match, and only satisfactory matches survive. Thereafter, job separation rates may decline (Jovanovic, 1979). Similarly, the acquisition of job or firm-specific skills implies a hazard rate that declines with job tenure (Becker, 1962; Mortensen, 1978).

The actual shape of the hazard rate out of temporary jobs is an empirical matter, as the theory above was never really intended for analysing temporary jobs and other specific contract types. To allow for non-monotonic variation in the hazards with job tenure, and to capture a wider range of possible effects of spell duration on the hazard rate, we use a flexible hazard function (e.g. Meyer, 1990; Lancaster, 1979, 1990). We only observe whether individuals leave their job within one-year intervals. The length of the job, T, is therefore assumed to be a discrete random variable.

Failing to control for unobserved heterogeneity in hazard models tends to create spurious negative duration dependence in the baseline hazard out of unemployment (Lancaster, 1979, 1990). This is due to the proportion of "stayers" in the risk set that tend to increase over time. Unobserved heterogeneity might also be important in hazard rates from employment (Farber, 1994). Unobservable characteristics, such as motivation, efforts, the propensity to shirk, or strong social or family pressure to remain employed may influence job tenure. Ignoring this unobserved heterogeneity can bias the effect of the covariates. In our analysis, we assume that unobserved heterogeneity is distributed according to a discrete probability distribution (Heckman and Singer, 1984).

2.1. The econometric model

A problem when estimating single risk duration models is a potential aggregation bias; individuals typically quit their job for different destinations. Restricting the estimated coefficients for the baseline hazard and the covariates to be the same for all destination states might therefore be an unduly restrictive assumption. Therefore, the econometric model for the sequence of discrete choice models is a multinomial logit model; in each period, the person can either stay in the temporary job (the reference case), become unemployed/nonparticipant, or find a permanent job.

Suppose a population entering a given state at time $T=0$, with Tbeing a positive discrete random variable associated to the duration in the state. The probability that the individual leaves the state in period t, conditional upon survival in the state up to time t, is the hazard function. Formally, it is written as

$$h(t) = Pr(T = t|T>t-1).$$

The overall survivor function can be written in terms of the interval specific survivor functions

$$\gamma_t = S(t|T>t-1) = Pr(T>t|T>t-1).$$

The survivor function at an arbitrary t is then

$$S(t) = \prod_{j=1}^{t} \gamma_j.$$

We assume that a person can exit a state to enter more than one destination. A person working in a temporary job can put an end to his (her) contract by getting a permanent job or by entering non-employment. Obviously, there is a duration associated to these two destinations: T_{PE}, i.e. the duration for time spent in a temporary job until getting a permanent job, and T_{NE}, i.e. the duration spent in temporary job until exiting to non-employment. We observe only the shorter of the two durations, thus we only observe $T=\min\,(T_{PE},\,T_{NE})$.

Let us assume that the discrete interval-specific hazard is multinomial logistic. With discrete duration data, the multinomial logit model can be seen as a proportional odds hazards model in a competing risks framework where $h_m(t)=\frac{\exp(Z_m(t))}{\sum_{j=1}^{3}\exp(Z(t))}$ where $h_m(t)$ denotes the hazard for exit into state m. m takes the values: (1) permanent employment (PE); (2) non-employment (NE, i.e. unemployment and non-participation); (3) temporary employment. $Z_m(t)$ is the timevarying index-function which accounts for the effect of the baseline hazard, observed and/or unobserved variables. We leave it for the moment unspecified.

Since simultaneous exits cannot occur, the overall hazard out of the state currently occupied is

$$h(t)=\sum_{j(t)\neq j(t-1)} h_j(t).$$

The conditional probability of survival can be therefore expressed as

$$\gamma_t = 1-h(t) = 1-\sum_{j(t)\neq j(t-1)} h_j(t).$$

The probability that an individual makes a transition into state m in period t, $P_m(t)$, can now be expressed as the product of the probability of survival until time $t$and the conditional probability of exiting to state m at time t,

$$P_m(t)=h_m(t)S(t-1)=\frac{\exp(Z_m(t)}{\sum\limits_{j=1}^{3}\exp\big(Z_j(t)\big)}S(t-1)\ m=1,\ldots,3.$$

Independence of the error terms of the utility functions for different choices is implicit in the standard multinomial logit model. This assumption leads to the restrictive Independence of Irrelevant Alternatives (IIA) property. To relax independence, unobserved heterogeneity is incorporated in our model.

We can now thus allow for both observed and unobserved heterogeneity in Z_m. Let us then define a 4×1 vector, D_t, consisting of four dummy variables, where only one of them is 1, corresponding to the duration being equal to either 1, 2, 3 or 4 years (the longest possible duration in the sample-in 1999 all observations are censored, see Section 3). Z_m is defined as $Z_m(t)=x_t'\beta^m+D_t'\gamma^m+\alpha^m$ where x_t denotes the observed vector of explanatory variables at time t; γ^m is a vector of the duration dependence parameters; and α^m is the destination state specific, time-constant, unobserved individual effect.

The transition probability-the destination specific hazard function-may now be written as

$$h_m(t|x_t,\alpha^m)=\frac{\exp\big(D_t'\gamma^m+x_t'\beta^m+\alpha^m\big)}{\sum\limits_{j=1}^{3}\exp\big(D_t'\gamma^j+x_t'\beta^j+\alpha^j\big)}.$$

To remove an indeterminacy in the model and to be able to identify parameters in the model, the parameter vector is measured relative to the departure state, i.e. $\theta_3=(\beta^3, \gamma^3, \alpha^3)$, are normalized to zero and this justifies the writing of the denominator as $1+\sum_{j=1}^{2}\exp\left(D_t'\gamma^j+x_t'\beta^j+\alpha^j\right)$; that is, we make temporary-jobs the base choice.

The likelihood contribution of a temporary job spell, conditional on unobserved variables, is

$$L(\beta,\gamma|\alpha)=\prod_{k=1}^{t}\frac{\exp\left[\left(D_k'\gamma^1+x_k'\beta^1+\alpha^1\right)c_k^1+\left(D_k'\gamma^2+x_k'\beta^2+\alpha^2\right)c_k^2\right]}{1+\sum_{j=1}^{2}\exp\left(D_k'\gamma^j+x_k'\beta^j+\alpha^j\right)}$$

where c_k^1, c_k^2 are indicators for making the transition to each of the two possible destination states- permanent job ($m=1$) or non-employment ($m=2$)- at time k. Temporary job spells that are still in progress at the end of the observation period are treated as right censored observations. For these observations, both destination indicators are 0, and thus, the contribution to the likelihood function is the probability of having held a temporary job for *at least*the observed number of years. This is a standard way of treating right censored observations in duration models.

To derive unconditional transition probabilities, we assume that unobservables are discretely distributed with unknown support points and that they are independent of observed characteristics.[5] Those points can be therefore interpreted as latent individual types. This multinomial logit model is semi-parametric in the sense that the discrete density of the random intercept serves as an approximation to any probability density (Heckman and Singer, 1984; Lindsay, 1995). The duration model is non-parametrically identified as it is essentially a panel data set with discrete outcomes, hence we are in essence estimating a random effects panel data model.

The likelihood contribution for an individual can be obtained by integrating the conditional likelihood distribution

$$L(\beta,\gamma,\alpha,p)=\sum_{s=1}^{2}L(\beta,\gamma|\alpha_s)p_s$$

where α are the location points (that can be interpreted as intercept for the baseline hazard function) and p is the associated probability, $s$being the number of location points. In the analyses below, the expressions above are trivially modified by the introduction of sample weights.

[5] This is a standard assumption in duration models although it may look restrictive. Indeed if it is incorrect for some variables, estimates could be biased by endogeneity. It would be desirable to have the unobservables correlated with those variables able to affect the probability of holding a particular contract for a given duration at a given time and test for endogeneity subsequently. However, identification in such models usually relies on the use of leads and lags in X_{it} in the equation for time t, which is only practical if there is sufficient variation over time in the regressors. Owing to the shortness of our panel, as there is not enough variation in the data over the four years, we assume independence of X_t and α. Finally, note that our specification is a purely reduced form model and although we are able to identify correlations, we are not necessarily able to identify causal relations between variables.

A note on the interpretation of the parameters is in order; The marginal effect of a certain variable, say, x_k , on the probability of entering state 1, say, is equal to

$$\partial P_1/\partial x_i = P_i\left(\beta_i^1 - \sum_{j=1}^{2} P_j\beta_i^j\right)$$

which is not necessarily of the same sign as the parameter involved. However, for most purposes, we are interested in the probability of leaving for a certain destination state relative to staying in a temporary job, the odds ratio, which is, say, P_1/P_0 The marginal effect of a variable x_k on the log odds ratio is

$$\partial \log\frac{P_1}{P_2}/\partial x_i = \beta_i^1.$$

Hence, when we interpret the results below, bear in mind that the parameter informs us about the probability of leaving a temporary job for a certain destination state relative to the probability of staying.

3. Data

The data used in the study are extracted from the waves 1994–1999 of the European Community Household Panel. The first year, however, serves only to determine the origin state, which is used as an explanatory variable, and the last year is only used to calculate destination states. Hence, the first observations in the employed sample are from 1995 and the last ones are from 1998. The data set contains more than half a million observations. After splitting the sample into men and women, and conditioning on belonging in the age group 16–64, the sample contains 238,421 observations for men and 284,730 observations for women.

We define temporary employment as jobs in "fixed contract durations", "Casual occupations" and 'Other working arrangement'. We are aware of the differences among those flexible arrangements especially concerning their legal treatment that is strictly country-based. We have grouped them in a wider category, in view of analysing the career prospects of those people holding work arrangements that are more "precarious" than the permanent ones. Given the number of observations, it would have been very difficult to treat them separately. Ordinary jobs are defined as those held by individuals responding "permanent job" when asked about the nature of their job. Finally, there are two more states an individual can occupy, namely unemployment and non-participation that we have merged to form the non-employment state, since they both correspond to mobility in the 'wrong' direction, namely, the direction leading potentially towards exclusion.

We select all those individuals who are in one of the categories corresponding to our definition of temporary employment. This results in a sample of 20,117 observations for men and 17,727 observations for women. For each observation, we know the origin state (what state did the individual occupy the previous year) and the destination state. This enables us to treat these data as (discrete time) duration data. Since data is annual, many temporary jobs are never observed in this sampling frame, as they have short durations by construction. We therefore oversample longer temporary jobs. Monthly flow data would have been ideal, but it was not possible to construct temporary job spells of monthly precision with the retrospective history available.

Right censoring is easily accommodated for as we have shown in the previous section. Leftcensoring-i.e. temporary job spells that were in progress when we the individual was interviewed for the first time-is a more complex issue (see D'Addio and Rosholm, 2002; D'Addio and Rosholm, 2004). To avoid its consequences, we have removed all left-censored spells of temporary employment. This leaves us with 14,226 observations of men and 13,190 observations of women.

Finally, we are interested in the extent to which some observed characteristics of individuals may explain the time they spend in temporary jobs and where they go subsequently. For some individuals, some of the necessary information is missing, and so we deleted those observations. In addition, because some variables are systematically missing in the dataset for some countries (e.g. job status, sector of occupation, health satisfaction), we excluded Germany, Luxembourg and Sweden. This leaves us with our final samples, which consist of 9,489 observations for men and 8,544 observations for women. There are 6,058 men in the sample, with a total of 6,587 temporary job spells. 2,013 of these spells end with a transition into a permanent job, while 1,021 end with a transition into non-employment. There are 5,834 women in the sample, with a total of 6,238 temporary job spells. 1,746 of these spells end with a transition into a permanent job, while 1,274 end with a transition into non-employment.

The dependent variable in the study is thus the number of years the individual spends in a temporary job and the subsequent destination state. In addition to the γ-parameters capturing duration dependence, the following explanatory variables are used in the analysis:[6]

Individual and job related characteristics:

A) An indicator for whether the individual was in unemployment/non-participation the previous year. The reference category is being in a permanent job.
B) A set of age group indicators (age 35–44 is the reference group)
C) Two educational indicators, one for having higher educational attainments, and one for having secondary education, the reference being primary education.
D) Two indicators for marital status, one for being married, one for being divorced, separated or widowed, and the reference group has never been married.
E) Eight different occupational codes; (1) Occ1 Legislators, senior officials and managers; (2) Occ2: Professionals ; (3) Occ3 Technicians and associate professionals; (4) Occ4 Clerical positions (REFERENCE CATEGORY); (5) Occ5 Service workers and shop and market sales workers; (6) Occ6 Skilled agricultural and fishery workers; (7) Occ7 Craft and related trades workers; (8) Occ8 Plant and machine operators and assemblers; (9) Occ9 Elementary occupations
F) Sector of occupation: Agriculture, Industry and Services

[6] Multicollinearity arising from problematic correlation between variables is excluded on the basis of various tests that we have carried out.

Table 1
Descriptive statistics by destination state-men and women

Variables	Men		Women	
	PE	NE	PE	NE
Temporary job duration (in years)	1.306	1.241	1.285	1.230
State occupied prior to entering TJ: 1 = Unemployment	0.281	0.593	0.318	0.630
AGE16-24	0.244	0.338	0.249	0.260
AGE25–34	0.418	0.329	0.401	0.379
AGE35–44	0.206	0.143	0.230	0.197
AGE45–54	0.107	0.125	0.112	0.117
AGE55–64	0.025	0.066	0.008	0.047
Higher education	0.208	0.112	0.277	0.172
Secondary education	0.314	0.241	0.332	0.349
Primary education	0.478	0.647	0.391	0.480
Married	0.431	0.372	0.420	0.478
Separated, divorced, widowed	0.037	0.032	0.072	0.077
Never married	0.533	0.596	0.508	0.445
OCC1	0.025	0.018	0.016	0.006
OCC2	0.074	0.054	0.150	0.061
OCC3	0.108	0.062	0.135	0.059
OCC4	0.091	0.060	0.229	0.215
OCC5	0.103	0.115	0.209	0.272
OCC6	0.023	0.043	0.008	0.021
OCC7	0.279	0.266	0.050	0.063
OCC8	0.167	0.109	0.051	0.049
OCC9	0.130	0.274	0.152	0.255
Agriculture	0.031	0.103	0.018	0.063
Manufacturing	0.478	0.429	0.190	0.171
Services	0.490	0.468	0.793	0.766
Firm size<20	0.468	0.567	0.443	0.567
Firm size 20–49	0.157	0.153	0.190	0.146
Firm size 49–100	0.097	0.088	0.100	0.097
Firms size 100–500	0.130	0.091	0.117	0.116
Firm size>500	0.148	0.101	0.150	0.074
Experience	13.240	13.831	11.693	12.134
Bad health	1.854	1.990	1.920	1.987
Public sector	0.122	0.163	0.262	0.225
Working hours	42.907	39.762	36.333	33.960
Part-time	0.032	0.117	0.187	0.287
Supervisory job status	0.046	0.024	0.024	0.011
Intermediate job status	0.125	0.074	0.091	0.066
Non supervisory	0.829	0.902	0.885	0.923
Training	0.244	0.247	0.320	0.264
Child aged less than 12	0.325	0.271	0.283	0.350
Gross monthly wage	1224.845	864.809	986.495	685.689
DK	0.025	0.015	0.020	0.018
NL	0.092	0.046	0.100	0.059
BE	0.025	0.009	0.040	0.022
FR	0.059	0.096	0.045	0.149
UK	0.175	0.136	0.192	0.079
IE	0.012	0.007	0.021	0.019
IT	0.160	0.171	0.168	0.171

(continued on next page)

Table 1 (*continued*)

Variables	Men		Women	
	PE	NE	PE	NE
GR	0.047	0.037	0.048	0.050
ES	0.294	0.429	0.243	0.342
PT	0.062	0.036	0.069	0.055
AT	0.040	0.008	0.039	0.017
FIN	0.010	0.009	0.014	0.018

Averages over the observation period 1994–1999; source: Our computations on Eurostat, ECHP; Germany, Sweden and Luxembourg excluded.

G) Four firm size indicators: less than 20 employees, 20–49, 50–99 (REFERENCE CATEGORY), 100–499, 500 or more
H) The monthly gross wage
I) Job status: Supervisory, Intermediate and Non-supervisory (REFERENCE CATEGORY)
J) Years of working experience
K) Received training during the past 12 months
L) Employed in the public sector
M) Has child less than 12
N) Works part-time
O) Bad health status (defined using the self-satisfaction indicator equal to 1)
P) The aggregate annual national real growth rate of GDP
Q) The average annual national unemployment rate
R) Country dummies (Spain being the reference).

Descriptive stat istics by destination state and for men and women respectively are reported in Table 1.[7]

The descriptive statistics reveal some useful insights. First, the youngest and the oldest are more likely to move into non-employment after a temporary job. Second, higher education levels as well as training seem to protect individuals against exclusion from the labour market. Third, single men are more likely than single women to face non-employment after atemporary job. Fourth, individuals in elementary occupations and in non-supervisory jobs are more at risk of becoming non-employed. The same occurs to (male) workers in small firms and in agriculture. Fifth, a temporary job in the public sector has different outcomes for men and women; while for men it is likely to lead to non-employment, the converse happens for women. Further, people holding temporary jobs after non-employment are more likely to experience non-employment again. Finally, workers either earning lower wages or working less hours when in a temporary job, are those more likely to enter subsequently non-employment. The same is true for those working part-time.

[7] Descriptive statistics for Spain, UK, and Denmark are available from the authors upon request.

4. Results

The estimates for the competing risks model are reported in Tables 2 and 3 for men and in Tables 4 and 5 for women.

Concerning unobserved heterogeneity (see Tables 3 and 5), we remark that the locations of the mass points are significant for both men and women. A simple likelihood

Table 2
Men's transitions without unobserved heterogeneity

	Permanent employment	Non-employment
γ_1	−4.9012** (0.3422)	−5.6380** (0.6032)
γ_2	−5.2682** (0.3450)	−5.4625** (0.6100)
γ_3	−5.1597** (0.3515)	−5.7494** (0.6323)
γ_4	−6.1958** (0.4236)	−6.6212** (0.7534)
Previous state: Non-employment	−0.4789** (0.0522)	0.8622** (0.0665)
AGE-25	−0.0213 (0.1022)	0.1331 (0.1300)
AGE25–34	−0.0665 (0.0742)	−0.0055 (0.0994)
AGE45–54	−0.3264** (0.0939)	0.1809 (0.1192)
AGE55–64	−0.8690** (0.1612)	0.5158** (0.1747)
Higher education	0.2521** (0.0647)	−0.5744** (0.0962)
Secondary education	0.3410** (0.0527)	−0.0933 (0.0698)
Married	0.1356* (0.0649)	−0.0662 (0.0860)
Widowed, divorced, separated	0.2387* (0.1227)	−0.0919 (0.1537)
OCC1	−0.2523 (0.1787)	0.9947** (0.2759)
OCC2	−0.7823** (0.1085)	0.0639 (0.1586)
OCC3	−0.3804** (0.0922)	−0.1953 (0.1428)
OCC5	−0.4837** (0.0957)	−0.1109 (0.1305)
OCC6	−0.5274** (0.1488)	−0.4554** (0.1644)
OCC7	−0.4427** (0.0870)	−0.0621 (0.1261)
OCC8	−0.2167** (0.0887)	−0.2224 (0.1320))
OCC9	−0.8334** (0.0905)	−0.1341 (0.1223)
Agriculture	−0.6087** (0.1407)	0.3487** (0.1002)
Services	0.0446 (0.0529)	0.0419 (0.0689)
FSIZE1	−0.0184 (0.0717)	0.0410 (0.0975)
FSIZE2	−0.0682 (0.0805)	−0.1248 (0.1096)
FSIZE4	0.0209 (0.0877)	−0.0760 (0.1230)
FSIZE5	−0.0977 (0.0819)	−0.2002 (0.1134)
Experience	0.0030 (0.0041)	0.0002 (0.0053)
Growth rate	0.1387** (0.0348)	−0.1413** (0.0461)
Unemployment rate	0.2281** (0.0183)	0.2913** (0.0279)
Bad health	−0.1198** (0.0287)	0.0463 (0.0337)
Public sector	−0.3647** (0.0704)	0.0783 (0.0810)
Working hours	0.0019 (0.0025)	−0.0091** (0.00.32)
Part-time	−0.4682** (0.1367)	0.1282 (0.1080)
Supervisory	−0.0589 (0.1172)	−0.2053 (0.1981)
Intermediate	0.2201** (0.0650)	−0.0831 (0.1005)
Training	0.1571** (0.0530)	0.1180 (0.0699)
Child less than 12	0.0133 (0.0547)	−0.0829 (0.0696)
Gross monthly wage	0.0000 (0.0000)	−0.0005** (0.0001)
Country dummies	Yes	Yes
Log-likelihood	−7365.6844	

Table 3
Men's transitions-with unobserved heterogeneity

	Permanent employment	Non-employment
γ_1	−5.7613** (0.5486)	−6.7718** (0.631)
γ_2	−5.9328** (0.554)	−6.3278** (0.6334)
γ_3	−4.6435** (0.559)	−5.4343** (0.6462)
γ_4	−5.3356** (0.6338)	−5.9399** (0.7937)
Previous state: Non-employment	−0.4187** (0.1025)	0.9522** (0.1187)
AGE–25	−0.3555 (0.202)	−0.2599 (0.2386)
AGE25–34	−0.1907 (0.1457)	−0.1977 (0.1785)
AGE45–54	−0.1712 (0.1875)	0.4047 (0.2166)
AGE55–64	−0.5391 (0.3143)	0.8092** (0.3333)
Higher education	−0.0379 (0.1526)	−0.8672** (0.1783)
Secondary education	0.2187* (0.1095)	−0.2296 (0.1257)
Married	0.1518 (0.1274)	−0.0336 (0.1569)
Widowed, divorced, separated	0.0101 (0.2108)	−0.3504 (0.2823)
OCC1	−0.1701 (0.384)	1.0283* (0.4697)
OCC2	−1.2024** (0.2257)	−0.2773 (0.2771)
OCC3	−0.6533** (0.2051)	−0.4926 (0.2538)
OCC5	−0.7526** (0.2058)	−0.2503 (0.2418)
OCC6	−0.9948** (0.3116)	−0.8682** (0.3242)
OCC7	−0.7955** (0.1957)	−0.3593 (0.2312)
OCC8	−0.6889** (0.1967)	−0.6816** (0.2369)
OCC9	−1.407** (0.1968)	−0.6476** (0.2276)
Agriculture	−0.5892** (0.2364)	0.3804 (0.2184)
Services	−0.0591 (0.1127)	−0.1229 (0.1469)
FSIZE1	−0.2987* (0.1479)	−0.2315 (0.1721)
FSIZE2	−0.2838 (0.1636)	−0.3457 (0.1904)
FSIZE4	−0.057 (0.178)	−0.1715 (0.2136)
FSIZE5	−0.3056 (0.1748)	−0.4138* (0.2101)
Experience	−0.010 (0.0085)	−0.0017 (0.0099)
Growth rate	−0.1037 (0.0636)	−0.3919** (0.0713)
Unemployment rate	0.2603** (0.029)	0.346** (0.033)
Bad health	−0.129* (0.0581)	0.0463 (0.0651)
Public sector	−0.4167* (0.1944)	0.0053 (0.3065)
Working hours	0.0006 (0.0006)	−0.014** (0.0062)
Part-time	−0.2219 (0.2367)	0.3606 (0.2284)
Supervisory	−0.0142 (0.236)	−0.1214 (0.3072)
Intermediate	−0.0093 (0.1375)	−0.3462** (0.1672)
Training	0.1687 (0.1123)	0.1796 (0.1288)
Child less than 12	−0.0787 (0.1115)	−0.1566 (0.1294)
Gross monthly wage	−0.0000** (0.0000)	−0.0006** (0.0001)
Country dummies	Yes	Yes
α^E	3.8258** (0.1376)	
α^{NE}	3.9491** (0.177)	
p_1	0.0653 (0.081)	
Log-likelihood	−6726.1068	

ratio test strongly rejects the model without unobserved heterogeneity, thus the introduction of unobserved heterogeneity clearly improves the likelihood value. Further, allowing for correlation between the two destinations, the specification with unobservables

Table 4
Women's transitions-without unobserved heterogeneity

	Permanent-employment	Non-employment
γ_1	−7.4407** (0.5452)	−8.481** (0.4483)
γ_2	−7.6581** (0.5461)	−8.2975** (0.4533)
γ_3	−8.0226** (0.554)	−8.9151** (0.4842)
γ_4	−8.0461** (0.5501)	−10.9722** (1.7818)
Previous state: Non-employment	−0.5624** (0.052)	0.6841** (0.068)
AGE–25	0.1365 (0.0927)	0.1744 (0.1075)
AGE25–34	0.1413* (0.0683)	0.2433** (0.0813)
AGE45–54	−0.1557 (0.0928)	0.2141* (0.1026)
AGE55–64	−1.8341** (0.2685)	0.4408** (0.1505)
Higher education	−0.0941 (0.0672)	0.0292 (0.0799)
Secondary education	0.1625** (0.0571)	0.3006** (0.0638)
Married	0.0982 (0.0618)	0.25** (0.0737)
Widowed, divorced, separated	0.1354 (0.0997)	0.4168** (0.1292)
OCC1	−0.1345 (0.1737)	−0.5551 (0.3562)
OCC2	−0.0281 (0.0793)	−0.4607** (0.1129)
OCC3	0.0362 (0.0733)	−0.5429** (0.117)
OCC5	−0.1619* (0.068)	−0.0142 (0.0748)
OCC6	−0.5841* (0.2731)	−0.3346 (0.1819)
OCC7	−0.407** (0.1259)	0.0283 (0.1363)
OCC8	−0.3304** (0.1141)	−0.2136 (0.1382)
OCC9	−0.3028** (0.0771)	−0.0109 (0.0831)
Agriculture	−0.9501** (0.2025)	0.1487 (0.143)
Services	−0.3561** (0.0727)	−0.236** (0.0909)
FSIZE1	−0.2201** (0.0751)	−0.0714 (0.0852)
FSIZE2	0.0487 (0.0835)	−0.1752 (0.1014)
FSIZE4	−0.1689 (0.0934)	−0.1002 (0.1045)
FSIZE5	−0.2155** (0.087)	−0.422** (0.1077)
Experience	0.0156** (0.0038)	0.0046 (0.0039)
Growth rate	0.2862** (0.0394)	0.2676** (0.0376)
Unemployment rate	0.3589** (0.0261)	0.3817** (0.0023)
Bad health	−0.1024** (0.0289)	−0.061 (0.0342)
Public sector	−0.2342** (0.0577)	0.06 (0.0672)
Working hours	0.0004 (0.0033)	−0.00018 (0.0005)
Part-time	−0.0935 (0.0806)	−0.1875* (0.096)
Supervisory	−0.2811** (0.1243)	−0.3146 (0.2076)
Intermediate	0.101 (0.0726)	0.23** (0.1002)
Training	−0.0173 (0.0515)	−0.0531 (0.062)
Child less than 12	−0.0335 (0.0574)	0.1612** (0.0639)
Gross monthly wage	0.0002 (0.0000)	−0.0007** (0.0007)
Country dummies	Yes	Yes
Log-likelihood	−7022.2452	

no longer imposes the IIA property, which is implicit in the standard multinomial logit model. We will therefore discuss uniquely the results obtained when unobservables are modelled (Tables 3 and 5).

We have represented graphically in Charts 1 and 2, the hazard functions for men and women, into permanent employment (PE) and non-employment (NE), respectively.

Table 5
Women's transitions – with unobserved heterogeneity

	Permanent employment	Non-employment
γ_1	−12.2455** (0.9422)	−14.044** (1.0097)
γ_2	−11.9846** (0.9474)	−13.3762** (1.0097)
γ_3	−11.4471** (0.9532)	−12.939** (1.0236)
γ_4	−11.4367** (0.965)	−15.1531** (1.461)
Previous state: Non-employment	−0.5566** (0.1082)	0.6714** (0.1241)
AGE–25	0.0085 (0.1176)	0.0733 (0.194)
AGE25–34	−0.0286 (0.1215)	0.0882 (0.1415)
AGE45–54	0.0328 (0.1837)	0.337 (0.2012)
AGE55–64	−1.9546** (0.3932)	0.4716 (0.3267)
Higher education	−0.1417 (0.146)	−0.0836 (0.164)
Secondary education	0.1087 (0.1183)	0.1885 (0.1284)
Married	−0.0346 (0.1152)	0.1401 (0.1396)
Widowed, divorced, separated	0.0012 (0.0557)	0.3211 (0.1913)
OCC1	−0.1607 (0.4121)	−0.7789 (0.5705)
OCC2	−0.0489 (0.1682)	−0.4615** (0.2048)
OCC3	−0.1565 (0.1636)	−0.7196** (0.2021)
OCC5	−0.1939 (0.1459)	−0.0186 (0.1643)
OCC6	−0.8136 (0.4635)	−0.655 (0.4311)
OCC7	−0.1953 (0.2502)	0.1713 (0.2744)
OCC8	−0.2933 (0.2528)	−0.2509 (0.279)
OCC9	−0.4695** (0.1595)	−0.2034 (0.1726)
Agriculture	−0.8569** (0.3335)	0.113 (0.3166)
Services	−0.3298** (0.1589)	−0.2853 (0.1739)
FSIZE1	−0.2412** (0.096)	−0.2036 (0.1445)
FSIZE2	−0.0016 (0.0574)	−0.2954** (0.1454)
FSIZE4	−0.1927 (0.1518)	−0.2529 (0.1939)
FSIZE5	−0.3542** (0.1465)	−0.6413** (0.2046)
Experience	0.0010 (0.0065)	0.0006 (0.0068)
Growth rate	0.2689** (0.0726)	0.289** (0.077)
Unemployment rate	0.5412** (0.0418)	0.610** (0.046)
Bad health	−0.0442 (0.0612)	−0.0345 (0.067)
Public sector	−0.2913** (0.0886)	0.0039 (0.0779)
Working hours	0.00047 (0.0007)	−0.0049 (0.0008)
Part-time	−0.0947 (0.1743)	−0.2826 (0.1971)
Supervisory	0.0939 (0.2936)	0.1244 (0.3893)
Intermediate	0.1654 (0.1634)	0.2917 (0.194)
Training	0.0396 (0.1042)	−0.0239 (0.1226)
Child less than 12	0.14 (0.1111)	0.3254** (0.1237)
Gross monthly wage	−0.0004 (0.0001)	−0.0009** (0.0002)
Country dummies	Yes	Yes
α^{E}	3.7213** (0.1208)	
α^{NE}	4.1071** (0.1607)	
p_1	0.1635* (0.0982)	
Log-likelihood	−6352.6007	

Both of them are non-monotonic. This pattern is not easily deducted looking at the γ-parameters. The reason is that duration dependence is influenced by both sets of parameters, through the denominator of the multinomial logit specification.

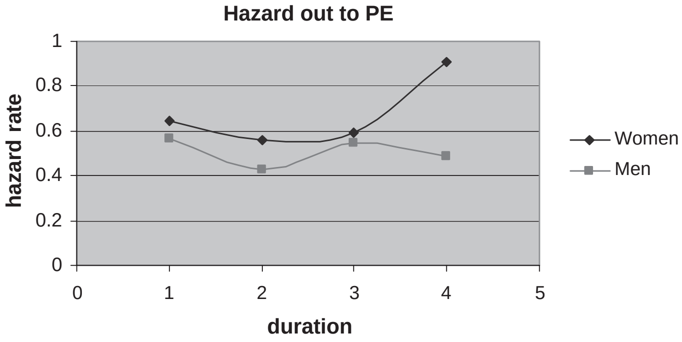

Chart 1. Hazard rates into PE for men and women.

When considering the conditional probability of exiting temporary jobs into permanent employment, we note that for men it increases after two years to decrease again after the third year. For women, the trend is similar for the first three years, but it has an opposite sign after that moment, implying that the longer the temporary job, the higher the probability of flowing into permanent jobs. Conversely, for men longer duration in temporary jobs decreases significantly their chances of subsequent job stability. The hazard rates into non-employment confirm this result and suggest different effects of temporary jobs for men and women. While they seem able to ease entry (or re-entry) of women into the labour market, they appear to represent a step into instability for men. We note however that temporary jobs of less than two years increase (decrease) the probability of flowing into non-employment (employment) of both groups, implying that very short contracts are not likely to lead to job stability of people that hold them.

Many significant differences across sexes appear. However, many characteristics seem to affect the hazard rates of the two groups in the same way. We focus on them first and discuss distinctive features subsequently.

1. Stepping into a temporary job after the experience of non-employment reduces the probability of getting a stable job afterwards. Symmetrically, it increases the probability

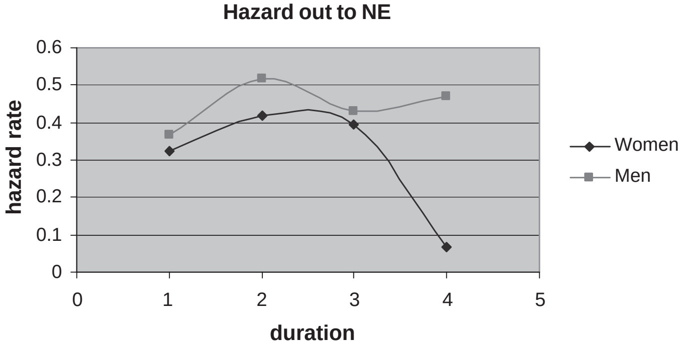

Chart 2. Hazard rates into NE for men and women.

of flowing into non-employment again. This result suggests the concept of "exclusion in work" as recently proposed in the literature,[8] i.e. the existence of a social risk in jobs that- instead of protecting those that hold them- is likely to keep those individuals in lasting and uninterrupted instability paths in and out of the labour market.
2. Temporary jobs held by individuals with low qualifications and in elementary occupations do not efficiently promote (re)-entry into the labour market. Conversely they seem to "promote" exclusion from it.
3. Older workers (compared to prime age individuals) have a higher risk of entering nonemployment. They also have lower chances of entering permanent employment. It thus seems that the older workers – rather than the young- are those who lose out in temporary jobs.
4. Temporary jobs in the public sector are associated with an increased risk of becoming non-employed. It is likely that in the public sector those jobs are used to accommodate temporary needs in terms of tasks and duration. The negative sign associated with this variable for both men and women in the transition into PE, points at the risk of such a practice. After a temporary contract in the public sector (compared to private) individuals are more likely to flow again into NE or temporary contracts.
5. Holding a temporary job in the agricultural sector (compared to manufacturing) reduces the probability of finding a permanent job and increases that of becoming non-employed. This result is certainly linked to season jobs and therefore it is quite understandable.
6. Temporary jobs in small firms might also worsen the chances of getting stable jobs in the future.
7. The unemployment rate has a positive impact on all transition probabilities. It is not so surprising when it comes to the transition into non-employment, but it is surprising for the transition into permanent jobs. It could imply that, when unemployment increases, temporary jobs are the first one to be destroyed by firms, thus generating an increasing outflow from temporary jobs in all directions.

We discuss now the distinctive determinants of men and women's transitions. First, note that many variables are significant in the characterization of men's transitions into PE and NE while they are not for women. Unobserved heterogeneity parameters suggest that for men's transitions, a large fraction of heterogeneity is captured by the included variables, while this result does not hold for women.

4.1. Results for men

Concerning wages, we see that the higher the wage, the lower is the probability of leaving the temporary job for *any*state. This is a straightforward reservation wage effect; when a job carries a high wage, the reservation wage is high and, correspondingly, the transition rate out of the state is low.

[8] See Desmarez et al. (2001).

The higher the occupational level, the lower is the transition rate into permanent jobs and the larger is the transition rate into non-employment. This could suggest that for higher occupational levels, holding a temporary job is stigmatising, while it is close to the norm for lower level occupations.

Concerning education, it appears that those with primary education have the largest risk of becoming non-employed and the lowest chances of finding a permanent job, suggesting that this group is at risk of exclusion.

The health status seems also to be important in men's transition rates. Having a bad perception of one's own health decreases significantly the probability of finding a stable job, and increases the one of being non-employed. This result is not surprising.

Good economic conditions (as measured by the GDP growth rate) are likely to reduce the probability of experiencing non-employment after a temporary job, while the effect on the probability of finding a permanent job is insignificant.

4.2. Results for women

Working in the service sector (compared to the manufacturing) reduces the chances of subsequent inclusion in the labour market. As to the part-time variable, its sign suggests that part-time does not (significantly) speed up the transition into PE, but at the same time it does not increase women's probability of becoming unemployed. Part-time could be potentially harmful when it is involuntarily, however in some situations it allows the flexibility necessary to strike a balance between working and family life.

Women with young children have a higher probability of flowing into NE after a temporary job. In modern societies that rest on increasing participation rates of the female workforce to contribute to alleviate the problem of population ageing, this seems a striking result. Further, it leads us naturally to wonder whether women with children voluntarily leave the labour market after a temporary job or if there exist some barriers that prevent them from entering it in a stable way. This is of course an unanswered question, but the puzzle surfaces in this study.

The GDP growth rate turns out to affect both transition probabilities positively, suggesting that in a cyclical upturn, there is some process of polarization going on among women.

5. Conclusions

We have analysed transitions from temporary jobs into permanent employment and nonemployment, using competing risks models in a discrete-time setting by specifying the hazard function to be multinomial logistic. Two specifications are estimated, one that does not allow for unobservables and one that does. Unobserved heterogeneity follows a discrete distribution. Introducing unobservables offers the opportunity of controlling for spurious duration dependence. We have adopted a flexible baseline hazard that varies freely.

The models have been estimated on the whole set of EU member states introducing a set of country dummies. The results show that labour market outcomes are affected by various factors and differ across sexes. Further, it appears that the passage through a flexible work arrangement is a different experience for men and women. The duration dependence parameters show that women with longer temporary contracts are more likely to get a permanent job, while for men after three years there is a clear negative path: transition rates into non-employment increase after that moment. While for men, long temporary jobs are in general associated with higher job insecurity, the converse is true for women. However, in view of the result discussed above, this occurs only for a limited category of women. Returning women, with children, are likely to be excluded again from the labour market.

We found that temporary jobs are often associated with low incomes, especially when the individuals step into those jobs after a spell of non-employment. Previous labour market status is thus important in determining job stability (and therefore of exclusion). For individuals entering a temporary job after the experience of non-employment, these look like dead-end jobs rather than stepping stones. The same is true for older workers and to some extent for the less educated (men).

Being rewarded with lower wages when in flexible work arrangements has of course a bear on the whole life of individuals. Owing to the higher risk of being exposed to unemployment, this most likely implies the lack of social means during the whole life: lower benefits when unemployed, lower pensions when retired, lower health protection and finally almost certainly higher poverty and exclusion risks. The concept of exclusion in work seems therefore particularly relevant in this context and especially for the most vulnerable individuals. Giving a job to individuals is not enough to improve their living conditions. It seems to us that mainly jobs that involve adequate training, allowing upgrading the qualifications and skills of the person hired, can make a difference.

The fact that lower wages are attached to temporary jobs could also affect future work decisions. If the arbitrage is between working and not working by comparing the levels of incomes in and out of work, individuals could decide that they are "better off" when unemployed (especially in countries with high levels of unemployment benefits) and therefore be "trapped" in that state.

Employment security and protection from dismissal may have a direct impact on job tenure. The view that workers should be protected from the loss of firm-specific capital has led many countries to introduce severance pay for dismissed workers. It has been claimed that this compensation has a depressing effect on employment and participation rates (Lazear, 1990). Bertola (1990) has contested this view and found no correlation between the strictness of an employment regime and average employment levels. We have not controlled for tightness of the employment regimes in the different countries owing to the high number of missing values in the relevant composite indicator. It seems, however, that owing to the temporary character associated with many jobs, firms use in reality flexible work arrangements as a means to escape the tightness of the employment legislation. In fact inflow into these jobs increases when labour market conditions are bad. This suggests the use of them to face some unexpected and higher workload charges (eventually to fill positions that are potentially temporary), and to face some rigidities in the labour market to quickly adjust.

Some occupational categories are likely to be more affected than others. It is generally the case for elementary occupations. Low skilled individuals face the same risk.

At the same time women with young children and older workers are more exposed to the risk of non-employment after the experience of a temporary job. This highlights the importance of policies target at balancing working and family life. For re-entering women it can also be important to upgrade their skills and qualifications, which may easily be the most efficient way to protect individuals from labour market exclusion.

In conclusion, we might be tempted to argue that when these jobs are held by vulnerable individuals they are not in general associated with positive labour market outcomes and may-on the contrary- be associated with instability and possibly exclusion. However, these results must be accompanied by a note of caution; the analyses carried out in this paper are descriptive in nature. In order to assess whether temporary jobs improve the situation of individuals holding these jobs, we need to estimate the counterfactual situation. In this case, the counterfactual situation is not obvious to us, and hence, to carry out such an analysis is left for future study.

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References

Becker, G., 1962. Investment in human capital: A theoretical analysis. Journal of Political Economy 70 (1), S9–S49.

Bentolila, S., Bertola, G., 1990. Firing costs and labour demand: How bad is eurosclerosis? Review of Economic Studies 57 (3), 381–402.

Bentolila, S., Saint-Paul, G., 1994. A model of labour demand with linear adjustment. Labour Economics 1, 303–326.

Bertola, G., 1990. Job security, employment, and wages. European Economic Review 34, 851–886.

Booth, A.L., 1997. An analysis of firing costs and their implications for unemployment policy. In: Snower, D., de la Dehesa, G. (Eds.), Unemployment Policy. Cambridge University Press, Cambridge, pp. 359–388.

Booth, A.L., Francesconi, M., and Frank, J., 2001. Temporary jobs: who gets them, what are they worth, and do they lead anywhere? ISER Working Paper No. 00-13. University of Essex, April.

Booth, A.L., Francesconi, M., Frank, J., 2002a. Temporary jobs: stepping stones or dead end jobs? Economic Journal 112, 480 (June).

Booth, A.L., Francesconi, M., Frank, J., 2002b., Labour as a Buffer: Do Temporary Workers Suffer?, ISER Working Paper 2002–29, University of Essex.

Burdett, K., 1978. A theory of employee job search and quit rates. American Economic Review 68 (1), 212–220.

Burdett, K., Mortensen, D.T., 1980. Search, layoffs and labor market equilibrium. Journal of Political Economy 88 (4), 652–672.

D'Addio, A.C., Rosholm, M. 2002. Left-censoring in Duration Data: Theory and Applications, Working Paper n° 2002–5, Department of Economics, University of Aarhus.

D'Addio, A.C., Rosholm, M., 2004. Left-censored Job Durations. Mimeo.

Desmarez, P. et al., .2001. Employment and Exclusion, final report, unpublished manuscript.

Devine, T.J., Kiefer, N.M., 1991. Empirical Labour Economics: The Search Approach. Oxford University Press, New York.

Dolado, J.J., Garcia-Serrano, C., Jimeno-Serrano, J.F., 2002. Drawing lessons from the boom of temporary jobs in spain. The Economic Journal.

European Commission, 2002. Employment in Europe, DG Employment and Social Affairs.

Farber, H., 1994. The analysis of interfirm worker mobility. Journal of Labor Economics 12, 554–594.

Heckman, J.J., 1981. Statistical models for discrete panel data. In: Manski, C.F., McFadden, D. (Eds.), Structural Analysis of Discrete Data with Econometric Applications. MIT Press, Cambridge, pp. 114–178.

Heckman, J.J., Singer, B., 1984. A Method of minimizing the distributional impact in econometric models for duration data. Econometrica 52, 271–320.

Jovanovic, B., 1979. Job matching and the theory of turnover. Journal of Political Economy 87 (5), 972–990.

Lazear, E.P., 1990. Job security provisions and employment. Quarterly Journal of Economics CV 3(422), 699–726.

Lancaster, T., 1979. Econometric Methods for the Analysis of Duration Data. Econometrica, vol. 47.

Lancaster, T., 1990. The Econometric Analysis of Transition Data. Cambridge University Press, Cambridge.

Lindsay, B.J., 1995. Mixture Models: Theory, Geometry, and Applications. NSF-CBMS Regional Conference Series in Probability and Statistics, vol. 5. (IMS-ASA).

Mortensen, D.T., 1978. Specific capital and labor turnover. Bell Journal of Economics 9 (2), 572–586.

Meyer, B.D., 1990. Unemployment Insurance and Unemployment Spells. Econometrica, 757–782 (July).

Petrongolo, B., Güell, M., 2001. Worker Transitions from Temporary to Permanent Employment: The Case of Spain.

Salverda, W., et al. 2001. The European-American Employment Gap, Wage, Inequality, Earnings Mobility and Skill; A Study for France, Germany, the Netherlands, the UK and the U.S., Final Report, Employment and Social Affairs, European Commission, June 2001.