

# Persistencies in the labour market

Paul Frijters\*  
Maarten Lindeboom†  
Gerard van den Berg‡

January 31, 2000

## Abstract

Using a longitudinal administrative tax-based panel, we look at several ways in which past labour market outcomes affect current labour market transition rates, termed *persistencies*. This includes loss-of skills during longer periods without a job and skill-accumulation during better paid long periods of employment. In the empirical model we use a flexible MPH-specification to analyse the transition rates between employment, unemployment, and non-participation. Allowing for three unobserved heterogeneity points for each possible transition, the most important finding is that during longer, better paid periods of employment, individuals' future transition rates into employment rose. Longer periods of non-employment generally decreased future transition rates, both to work and from work, especially if the cumulative period of non-employment was more than 2 years.

Theme: micro-economics of unemployment

Keywords: duration analysis; hysteresis, learning.

JEL-code: C41, J22 J64

---

\*Corresponding author. Free University Amsterdam and Tinbergen Institute. Faculty of Economics, Room 2A-24, de Boelelaan 1105, 1081 HV Amsterdam, pfrijters@econ.vu.nl.

†Free University Amsterdam and Tinbergen Institute.

‡Free University Amsterdam, CEPR, and Tinbergen Institute.

# 1 Introduction

Using a longitudinal administrative tax-based panel, we look at the relationships between past labour market outcomes and current labour market transition rates, which are called *persistencies*. One persistency that has attracted a lot of attention is the effect of longer spells of unemployment on future transition rates. In the hysteresis-literature (see e.g. the 25 articles in Roed, 1995), several mechanisms are suggested through which spells of unemployment negatively affect future labour market outcomes. One is the classic argument of Phelps (1972) that individuals lose their skills during unemployment which negatively affects future possibilities of finding a job. This line of reasoning was recently advanced by Lundqvist and Sargent (1998) to explain European unemployment levels. Other possible negative effects of longer spells of unemployment are discouragement, stigma, or an adaptation of social norms (e.g. Pioré, 1972; or Lindbeck, 1995).

In empirical work though, only little evidence has been found that longer spells of unemployment permanently negatively affect future labour market opportunities. Heckman and Singer (1980), on the basis of 122 individuals, found no effect of previous spells of unemployment on current hazard rates from unemployment to employment. Whilst Lynch (1985, 1989) also finds no effects, Omori (1997) and Blau (1994), who allow for more flexible unobserved heterogeneity specifications, do find some effects. Omori finds a clear negative effect of long spells of unemployment on future transition rates to work in the NYLS-data, whereas Blau finds several effects of past labour market outcomes on current labour market opportunities of the elderly, but no general pattern.

A related persistency of empirical interest has been whether individuals learn extra skills in good jobs, which can increase both future wages and future transition rates into job, for instance due to more contacts. Several recent studies indeed indicate that productivity-skills increase during the tenure of many jobs (e.g. Dustmann and Meghir, 1999, and the references therein). A study by Bonnal et al. (1997) on the effect of unemployment training programs in France indicates that the long-term effects of training the unemployed or giving the unemployed low-paid jobs are small though, suggesting a possible relationship between the amount of learning that takes place in jobs and the level of income in those jobs.

In the Dutch panel data set we use to empirically assess these two persistencies, the labour market spells of about 65000 adults are recorded over

the period January 1989 through December 1997. In order to avoid initial conditions problems, we will use the 4897 individuals whose entrance into the labour market we can observe. Extensive information is available about the sources of incomes and household composition of individuals during this period, though not much is known about individual characteristics. In the empirical model we use a flexible MPH-specification to analyse the transition rates between employment, unemployment, and non-participation.

In the second section, the data set used is described and the model is presented. In the third section the findings are discussed, some simulations are done to reveal the most interesting aspects of the findings, and some model-variants are presented to assess the robustness of the results and the value of the methods employed. The final section concludes.

## 2 Data and method

### 2.1 data

About 6% of the tax-records of the Dutch population (randomly selected) in the period January 1, 1989, through December 31, 1997, are stored in the Income Panel data base. This includes information on all the spells of about 65000 adults aged 15 to 55. A spell indicates a particular ‘source of income’, which includes wages, unemployment benefits, welfare benefits, disability allowance, benefits+other sources of income (such as alimony, pensions or payments by the previous employer), etc. In all, 15 types of sources of income are differentiated. We reduce these 15 sources of income to three distinct states: *work*, defined as having income from work or profits; *unemployment*, defined as having amongst the sources of income an unemployment benefit level; and *non-participation*, defined as all other types of benefits, unspecified sources of income or no-income. In order to avoid initial conditions problems, we use only the 4897 adults for whom we observe the time that they become active on the labour market. The summary statistics of the individuals in their first spells are then given in Table 1.

The results in this table show that most individuals live in a household with more than 1 individual, that average incomes in unemployment are rather higher than average incomes in work (though there is an obvious age-difference between workers and the unemployed), and that most of the labour-market entrants who live in households with children start in the work

Table 1: summary statistics of individuals in the Income Panel data set at entry

	current state	Work	Unemployment	Non-participation	Total
Variables					
Age		17.4	22.1	18.4	17.9
Female		0.50	0.46	0.48	0.49
ln(taxable income per day in Dutch guilders)		2.59	3.41	0.42	2.09
number of children in household		1.13	0.46	0.83	1.03
Living together		0.94	0.67	0.89	0.92
Living in one of the 4 major cities		0.13	0.22	0.16	0.14
Individuals in percentages of whole		71%	4%	25%	

state. The table also shows that 71% of the entrants immediately has a job, probably straight out of school. The fact that there are some people who are observed to start in unemployment, even though they have no previous tax-record, is somewhat puzzling, because in the Dutch welfare system unemployment benefits are only given to individuals who have previously worked. Individuals without a job who have never worked are given a general welfare benefit and are denoted as non-participants in this paper. The small number of entrants into unemployment have therefore probably had some previous incomes that were enough to qualify for unemployment benefits (such as odd jobs for work agencies), but not high enough to have previous tax records. After finishing school, they then claimed unemployment benefits. It is open for debate how we should view such individuals, but here we choose to see them as new entrants in unemployment.

The rough flows between the three states in the whole period are given in Table 2.

We can see that each individual experiences about 3 states on average in this period, which allows a careful look at the effect of previous outcomes (lengths of spells and incomes during these spells) on transition rates. It is also clear that the number of individual characteristics available is rather scant. In particular, there is no direct information available on education. As a proxy, we will use the age at which an individual enters the labour market. Also the information on incomes is restricted to the daily average income during a spell. Finally, entitlements to benefits are not known and cannot be computed accurately, for one because the number of hours worked

Table 2: the flows between the three labour market states for individuals in the Income Panel data set, in the period 1989-1997

	destination	work	unemployed	non-part.	right-censored	Total
Source:						
work		0	1214	4206	3059	8479
unemployed		1162	0	210	202	1574
non-participation		3807	163	0	1637	5607
Total		4969	1377	4416	4898	15660

(relevant for many benefits) is not known.

## 2.2 Method

Having the three states, an extended MPH-model is used. For the hazard rate we take

$$\theta_j^w(t_{i,m_w}^w | \lambda_{i,j}^w, x_{i,m_w}, wh_{i,m_w}^w, \tau_{i,m_w}^w) = \lambda_{i,j}^w b_j^w(x_{i,m_w}) z_j^{w'}(t_{i,m_w}^w) h_j^w(wh_{i,m_w}^w) c_j^{w'}(\tau_{i,m_w}^w + t_{i,m_w}^w)$$

$j \in \{u, o\}$ . Here  $\theta_u^w$  denotes the hazard rate from work to unemployment and  $\theta_o^w$  the hazard rate from work to non-participation.  $t_{i,m_w}^w$  denotes the length of the current spell in work, which is the  $m^{th}$  observed spell in work;  $x_{i,m_w}$  denotes a vector of observed characteristics at the start of the spell;  $\lambda_{i,j}^w$  denotes an unobserved characteristic of individual  $i$  for the hazard from work to state  $j$  ( $\lambda_{i,j}^w > 0$ ) which differs over  $j$ ;  $wh_{i,m_w}^w$  denotes a vector of variables that capture the labour market history of individual  $i$  relevant for the hazard from work;  $\tau_{i,m_w}^w$  denotes the calendar time at which the current spell in work began;  $z'(\cdot)$ ,  $b(\cdot)$ ,  $h(\cdot)$ , and  $c'(\cdot)$  are non-negative functions denoting, respectively, the baseline hazard, a function of observable characteristics, a function of previous labour market histories and a function of calendar time.

For individuals in unemployment, we have:

$$\theta_l^u(t_{i,m_u}^u | \lambda_{i,l}^u, x_{i,m_u}, wh_{i,m_u}^u, \tau_{i,m_u}^u) = \lambda_{i,l}^u b_l^u(x_{i,m_u}) z_l^{u'}(t_{i,m_u}^u) h_l^u(wh_{i,m_u}^u) c_l^{u'}(\tau_{i,m_u}^u + t_{i,m_u}^u)$$

$l \in \{w, o\}$ . Here  $\theta_t^u$  denotes the hazard from unemployment to state  $l$ . The functions and variables are otherwise analogue to the functions defined in the hazard rate from work. A similar hazard rate specification holds for the transitions from non-participation.

Focussing only on those individuals who entered the labour market during the examined period, there are no initial conditions problems. The likelihood becomes

$$\begin{aligned}
L_i = & \prod_{i=1}^N \sum_k \{ p_k * \prod_{s=1}^{n_i^w} \prod_{j_s \in \{u, o\}} \theta_{i,j_s}^w (T_{i,s}^w | \lambda_k)^{I_{T_{i,s}^w}} e^{-\int_0^{T_{i,j_s}^w} \theta_{i,j_s}^w dt} \\
& * \prod_{s=1}^{n_i^u} \prod_{j \in \{w, o\}} \theta_{i,j,s}^u (T_{i,s}^u | \lambda_k)^{I_{T_{i,s}^u}} e^{-\int_0^{T_{i,s}^u} \theta_{i,j,s}^u dt} \\
& * \prod_{s=1}^{n_i^o} \prod_{j \in \{u, w\}} \theta_{i,j,s}^o (T_{i,s}^o | \lambda_k)^{I_{T_{i,s}^o}} e^{-\int_0^{T_{i,s}^o} \theta_{i,j,s}^o dt} \}
\end{aligned}$$

where  $\theta_{i,j_s}^w$  is shorthand for  $\theta_{i,j_s}^w (T_{i,s}^w | \lambda_{i,j}, x_{i,m_w}, wh_{i,m_w}^w, \tau_{i,m_w}^w)$  and  $T_{i,s}^w$  denotes the observed duration of individual  $i$  in the  $s^{th}$  observed workspell of this individual. Also,  $\lambda_k$  denotes the heterogeneity term corresponding to probability point  $k$ .  $I_m$  is an indicator function which equals one if the spell  $m$  is completed and equals zero if it is right-censored. The total number of spells of an individual equals  $n_i^w + n_i^u + n_i^o$ , whose observed maximum is 22.

### 2.2.1 Specification:

The baseline function  $z'(t)$  is taken to be piece-wise constant, where we fix the first piece for normalisation purposes;  $c'(\tau + t)$  is also piece-wise constant and allows only for two seasons: before April 2 in a year and after. Given that the Dutch GNP per person was growing steadily at around 2% a year for most of this period, we do not include business-cycle indicators, although we do control for a trend by including a year of entry. Hence we have

$$c'(\tau + t) = e^{s_0 * I_{0 \leq (\tau+t) \bmod 365 < 92} + s_1 * I_{91 < (\tau+t) \bmod 365} + s_2 (\text{year of entry} - 1989)}$$

The other functions  $b(x)$  and  $h(\cdot)$  are taken to be exponentially linear, i.e.,  $b(x) = e^{\alpha x}$ .

As individual regressors we have indicator functions of the gender, the type of location an individual lives in at the start of a spell (in one of the four largest cities or otherwise), and of whether an individual is single or not. Also, we have the number of children for which an individual gets benefits (which is usually all children below 18 years), the age at the start of a spell, the age at which the individual entered the labour market and the average income in the current spell. Some interaction terms are added.

As indicators of labour market histories we use cumulative time spent out of work, cumulative time spent in work, the previous non-work duration, the previous work duration, the income in the previous job, the income in the previous non-job, and cumulative income.

Each individual has 6 unobserved characteristics, corresponding to the six possible transitions. We take the most flexible approach by assuming that each unobserved heterogeneity distribution  $F_j^x$  corresponding to the hazard rates from state  $x$  to state  $j$ , has a fixed number of mass-points. Though other specifications will be discussed later, in the final specification shown, each distribution  $F_j^x$  consists of three points ( $\lambda_{j,1}^x$ ,  $\lambda_{j,2}^x$  and  $\lambda_{j,3}^x$ ). This means there are  $3 \cdot 6$  heterogeneity points and  $3^6$  possible combinations of these heterogeneity points that an individual can have. As this exceeds the number of observations, we restrict the probability distribution between these points. We assume that  $P[\lambda_j^x = \lambda_{j,m}^x, \lambda_k^x = \lambda_{k,n}^x] = 0$  for  $n \neq m$ , where  $j$  and  $k$  denote the two different exits of the same state  $x$ . For the heterogeneity distribution of the two exits from one state, this means we estimate three mass points in the two-dimensional plane of the heterogeneity distribution of the two exits. We impose no restrictions on the values of the heterogeneity points (no one-factor loading). This avoids the problem identified by Van der Berg and Lindeboom (1998) of one-factor loading models that they implicitly assume a fixed relationship between the variance of each marginal heterogeneity distribution and the correlation structure between the heterogeneity distributions  $F$ . Making no further assumptions on the probability distribution of the heterogeneity points, we are left with 27 possible combinations of individual heterogeneity points.

### 3 Results

In Table 3 the results of the final specification are given.

Table 3: Results of the persistence model for Dutch labour market entrants.

Variables \	State	Work		Unemployed		Non-part	
	exit-state	Unemployed	Non-part	Work	Non-part	Work	Unemployed
Individual characteristics							
Living together (0=no,1=yes)		-0.10	-0.27**	0.32**	-0.02	0.14**	-0.11
ln(age)		-0.38	-1.40**	-2.76**	0.17	1.39**	3.04*
gender (1=female)		-0.07	-0.06	-0.14*	0.10	-0.08*	-0.03
ln(max(daily income,1))		0.189**	-0.42**	-.64**	-0.24*	-0.27**	-0.12**
# kids		-0.06	0.04*	-0.00	-0.13	-0.11**	-0.15
# kids*(gender)		0.02	-0.02	-0.08	0.03	0.01	-0.23
Big city (1=yes)		0.12	-0.03	-0.39**	0.18	-0.04	0.38*
age at entry*work <sup>a</sup>		0.64	1.43**	0.79	1.12	-3.52**	2.49
age at entry*not-work		0.71	1.45**	0.79	1.23	-3.39**	2.63*
entry year of current spell		-0.11**	0.07**	0.04**	0.28**	-0.01	-0.18**
Baseline							
till day 32		-8.62	-5.58	-5.53	-8.63	-5.83	-8.20
day 33-63		-8.73**	-6.32**	-5.53**	-8.32**	-5.97**	-9.17**
day 64-155		-8.28**	-6.34**	-5.42**	-7.58**	-5.55**	-9.12**
day 155-366		-8.52**	-6.50**	-5.86**	-7.29**	-5.79**	-9.02**
after day 365		-8.84**	-4.96**	-5.30**	-7.81**	-5.34**	-8.41**
Season							
After April 1		0.10	1.09**	0.23**	0.60**	0.74**	0.65**
Persistence-effects							
ln(cum. nw duration) <sup>b</sup>		-0.04	-0.02	0.23**	0.13	0.06*	-0.13
cum. nw dur > 6 mnd?		0.12	-0.06	-0.11	-0.00	-0.18**	0.25
cum nw dur > 1 jr?		-0.06	0.10	-0.03	-0.20	0.12*	0.16
cum nw dur > 2 jr?		-0.50**	-0.36**	-0.19	-0.09	-0.01	0.11
cum nw dur > 3 jr?		-0.08	0.03	0.17	0.03	-0.16*	-0.34
ln(cum. work dur)		0.23**	0.12**	0.05	-0.01	0.02	0.29**
ln(previous non-work dur)		0.09*	0.18**	-0.18**	-0.07	-0.09**	0.02
ln(prev. work dur)		-0.13**	-0.04	0.19**	0.02	0.06**	-0.05
ln(Income prev. job)		0.05	-0.05**	0.12**	-0.15	0.08**	0.09
ln(Income prev. non-work)		0.15**	-0.42**	-0.11**	-0.06	-0.08**	0.19**
ln(cum income)		-0.03	0.02	-0.10*	0.01	0.01	-0.04
Heterogeneity points							
point 1		2.59**	8 0.60**	0.25**	1.26**	0.19**	0.37**
point 2		0.21**	0.22**	0.10**	1.35**	0.44**	0.52**
point 3		0.45**	0.13**	0.39**	0.96**	0.13**	0.05**
Average Log likelihood				-17.510			
Percentages of total # spells		50%		18%		34%	

<sup>a</sup> Interaction of age at entry and whether the first state was in work<sup>b</sup> Total duration without a job. \* signif at 5%, \*\* signif. at 1 %



Most of the found effects of individual characteristics are not surprising. An exception is the insignificance of gender and the number of children on transition rates: though a higher number of children does, as expected, reduce transition rates out of non-participation (especially for women), the effects are not very significant or large. This signals that one of the main peculiarities of the Dutch labour market in previous decades, i.e., persistently low labour market participation levels of women (especially those with children), is a thing of the past for the new cohort studied here.

The baseline hazards show some marked non-linearities, with perhaps the most striking the fact that baseline transition rates from work to non-participation are a lot higher after one year than they were just before the end of a year. Perhaps this reflects the fact that many benefits within the non-participation state, such as long-term disability allowances, are only available after several years of work. That transition rates of the unemployed to work are rather constant, whilst the transition rates into non-participation increase over time are also not surprising as the possibility of claiming unemployment benefit disappears after a while. The seasonal effect shows that mobility is substantially lower during the colder months of the year (before April).

The longer the previous work duration, the lower the transition rates out of work. A higher cumulative work duration has the opposite effect. This means that a high cumulative work duration concentrated in the last work spell has much less effect on the exit rates out of employment than a high cumulative work duration spread over many work spells. Long un-interrupted spells of employment hence do not lead to positive persistencies.

In general, the income persistencies are also clear: the higher previous incomes in non-employment, the lower the exit rates into work, and the higher the exit rates into unemployment. Because incomes in non-employment are strongly related to benefit levels, this signals a 'pull-effect' from higher benefits into unemployment. A high income during work increases future transition rates into work from the other states which suggests that individuals pick up 'job-finding skills', such as contacts, during well-paid spells of employment. Also, those with a high income in previous job have a lower transition rates into non-participation. In comparison, the effects of cumulative income are small, though there is some indication that unemployed individuals who have earned a lot in the past, are more likely to go into non-participation than to work, perhaps representing a wealth effect for the demand for leisure.

The duration persistencies are less clear: the longer the previous time spent out of employment, the lower the exit rates from work, especially when

the time spent in non-employment is spread out over several spells (which reduces the counterbalancing effect from the previous non-work duration).<sup>1</sup> Especially individuals who have been without employment for more than 2 years have lower exit rates out of employment, perhaps signalling that 2 years is a switching point, after which individuals tend to search for more secure jobs (having had insecure jobs in the past). It also happens to be the case that a previous cumulative non-employment duration above two years reduces exit rates to work. 2 a cumulative time of two years without work hence seems a turning point with respect to future possibilities of finding a job. Those with such high cumulative non-employment that do find a job have lower transition rates out of a job.

The net effect of longer previous spells of non-employment on transition rates to work are negative. Hence, it does seem that some skills are being lost during unemployment, especially during a long uninterrupted spell of non-employment (which increases the effect of previous non-employment). Apart from this negative effect of non-employment, the effect of longer spells without a job probably has a second negative persistency via the effect of long non-employment on future wages (see appendix for a basic analysis).

Because the effects of longer durations are highly non-linear, we look at the actual impact of previous durations and incomes on current transition rates for some selected examples. In the following graphs, we focus solely on the persistence function  $h(\cdot)$ , which we compute for three examples. In the first example we focus on  $h_w^u(\cdot)$ , i.e., the persistence effect for an individual in the transition rate from unemployment to work. We show this function for an individual who enters the labour market into non-participation at  $t_0$ , finds employment 24 months later (at  $t_1$ ), then goes to unemployment 12 months later ( $t_1$ ), and moves to non-participation 4 years later ( $t_3$ ). The two lines shown reflects whether the individual obtains a mean income in all states or a double mean income in both states, which shows the importance of the income persistencies:

---

<sup>1</sup>Though the effect of the last non-employment spell on transition rates is positive, this effect is always smaller than that of the cumulative amount of time spent without a job. It does indicate though that individuals who move often between unemployment and non-participation during a long period of non-employment, lose less skills than individuals who are not mobile during a long period of non-employment.

### The persistence function for unemployment to work

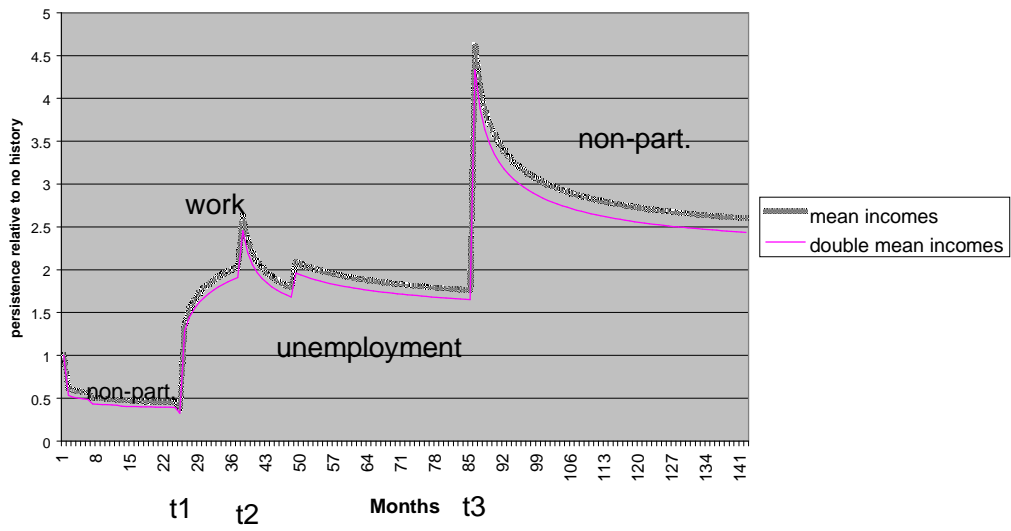


Figure 1:

The shown line reflects the persistency in the transition from unemployment to work someone would have at that moment with that history. Hence the value of about 1.6 at 30 months implies that an individual who would at that moment become unemployed with his history so far, would have a 60% higher exit rate to work relative to an otherwise identical individual with no history. It is obviously impossible to become unemployed when one already is unemployed. Hence the change in the persistence during a spell of unemployment shows the effect on future spells of unemployment (which by necessity involves at least one more spell in another state).

The graph shows that a spell of work greatly increases the future transition rate from unemployment into work. Also it shows that future transition rates reduce with duration of a spell of non-employment when the spell is still short. After about 6 months to a year, the effect of further increases in duration of non-employment on transition rates from unemployment to work is small. The jump in  $h_w^u(\cdot)$  at  $t_3$  is mainly due to the negative effect of non-employment incomes: because incomes in unemployment are a lot higher than in non-participation, the transition rate from unemployment to work is higher for someone who was just in non-participation than for someone whose previous non-employment spell was unemployment, possibly because of a greater motivation. The effect of greater incomes on persistencies for this transition rate seems quite small, where we have to bare in mind that both work incomes and non-work incomes here are double mean. From the estimated coefficients we could already see that higher work incomes increase future transition rates to work whereas higher non-work incomes can have opposite effects.

In the second example, we show  $h_w^o(\cdot)$  (persistencies from non-participation to work) for an individual with a particular history:

The persistence function for non-participation to work

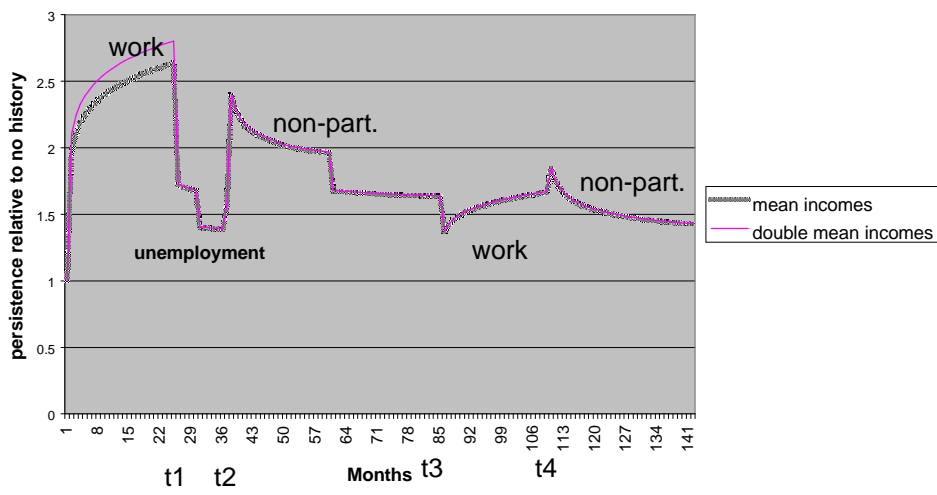


Figure 2:

The persistence function for work to unemployment

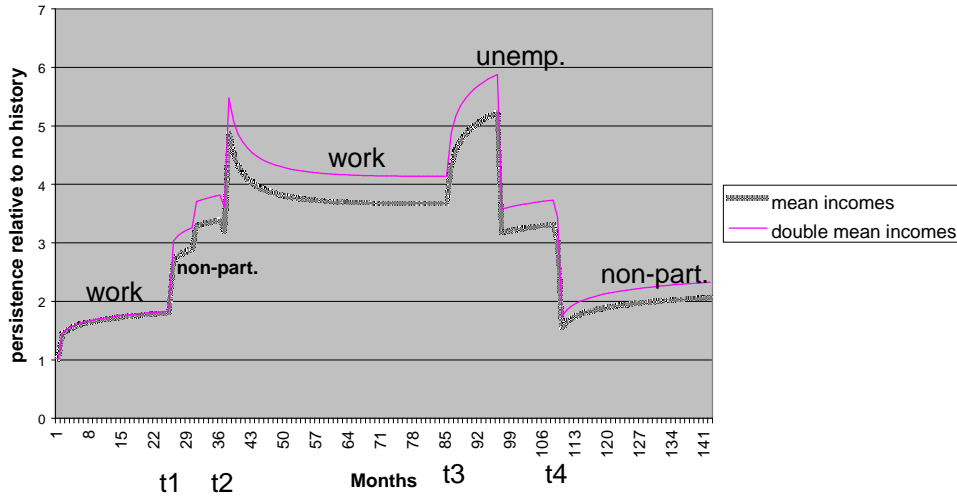


Figure 3:

In the first spells of unemployment and non-participation, we clearly see the non-linearities in the effect of cumulative time in non-employment on this transition rate: after 6 months and 3 years, the transition rate drops substantially, possibly related to discouragement: individuals with previous long spells of non-employment have a lower  $h_u^w(\cdot)$ . Again, the big decrease in the transition rates due to a spell of unemployment is mostly related to the fact that the income in unemployment is quite high which reduces the future transition rate from non-participation to work. Indeed, we can see that higher work-incomes increase the future transition rate from non-participation to work, whilst higher unemployment-incomes reduce it.

In the last example, we show  $h_u^w(\cdot)$  (persistencies from work to unemployment) for a particular work history:

Here we see that the future transition rate from work to unemployment increases with short previous spells of work. Though this may reflect a stigma-effect, it is also plausible that it involves some residual unobserved heterogeneity the model has failed to pick up. The income effects are also marked: individuals with higher previous work-incomes have a lot higher exit rates to unemployment. Because unemployment entitlements are directly related to previous pay, this is not that surprising and may represent a pull-effect from higher benefits. The non-linearities are again quite strong: just after two years and three years of cumulative non-employment, future transition rates to unemployment drop markedly.

Because the total impact of some of these persistencies depend on all the characteristics of all individuals due to the non-linear specification, we need to look at simulations in which we turn some of the persistencies off if we want to get a feeling for the importance of the persistencies on labour participation rates. Therefore we look at two selected counterfactuals. In the first scenario we simply simulate for 10000 individuals what the percentage of individuals in employment of different ages would be if the model held forever. The full procedure, involving imputed incomes and endogenous changes in personal characteristics, is explained in the appendix. In the second scenario, we compute what would happen if there would be no effect from previous incomes in work and cumulative incomes, essentially keeping these values at zeros for the persistence function. In the third scenario we calculate what would happen if the duration of previous spells of non-employment would not have any effect by keeping them at zero. The results are shown in the next graph in terms of labour market participation levels under the different scenarios.

Firstly we may see that the percentage of individuals in employment (=labour participation level) in the baseline simulation is the lowest for individuals aged about 20, which is when a large glut of school leavers enters the labour market. Individuals entering the labour market before that age more often start in employment than the individuals who enter at 20. The average estimated labour participation level of about 70% for adult males fits the national average.

As we can see, the effect of omitting the income persistencies reduces labour participation levels for individuals in the age range from 17 to 30. In this range the positive persistencies from work dominate. After this age range, the participation levels are even higher without income persistencies. This is probably due to the fact that individuals with high previous incomes

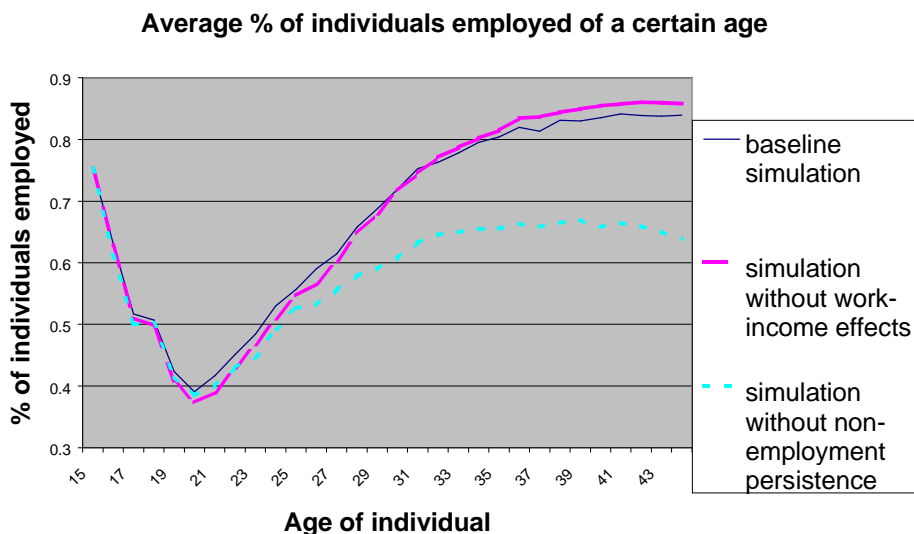


Figure 4:

have a reduced transition rate from work to unemployment.

For the persistencies from non-employment spells the results are clearer in the sense that labour market participation levels are a lot lower for all individuals above 20 without these persistencies. The net effect of previous spells of non-employment on current employment levels is hence positive. One positive persistence that can be observed from Table 3 is that longer cumulative spells (above 2 years) of non-employment decrease transition rates from work. This apparently outweighs the negative effect of longer periods of non-employment on future transition rates from unemployment and non-participation to work.

### 3.1 Model-variations

In this sub-section we assess the importance of the flexibility of the unobserved heterogeneity distribution. We look at three different cases, ever more restrictive of the heterogeneity distribution:

1. Each  $F_j^x$  has two mass-points. We only restrict the probability distribution of the exits from unemployment such that  $P[\lambda_{j,i}^u = \lambda_{j,m}^u, \lambda_{k,i}^u = \lambda_{k,n}^u] = 0$



iff  $n \neq m$ . This leaves 12 heterogeneity points and 32 probability points to be estimated. A version in which there were no restrictions on the probability distribution did not converge.

2. Each  $F_j^x$  has three mass-points and  $P[\lambda_{j,i}^x = \lambda_{j,m}^x, \lambda_{k,i}^y = \lambda_{k,n}^y] = 0$  iff  $n \neq m$  for all  $x$  and  $y$ . Hence there are then 18 heterogeneity points and only three probability points to be estimated.

3. Each  $F_j^x$  has two mass-points and  $P[\lambda_{j,i}^x = \lambda_{j,m}^x, \lambda_{k,i}^y = \lambda_{k,n}^y] = 0$  iff  $n \neq m$  for all  $x$  and  $y$ . There are then 12 heterogeneity points and only two probability points to be estimated.

The next table shows the found heterogeneity points under each of these three specifications.

Table 4: heterogeneity points found under different specifications

	Work		Unemployment		Other		Average Log-lik	Number of params
	unem.	other	work	other	work	unem.		
Specif. 1							-17.5280	193
point 1	2.32	0.46	0.28	0.80	0.27	0.20		
point 2	0.25	0.10	0.25	0.66	0.30	0.18		
Specif. 2							-17.5149	170
point 1	2.41	0.60	0.30	0.82	0.23	0.40		
point 2	0.23	0.22	0.13	0.94	0.55	0.52		
point 3	0.45	0.12	0.46	0.85	0.16	0.06		
Specif. 3							-17.5298	163
point 1	2.25	0.61	0.15	0.70	0.20	0.33		
point 2	0.38	0.17	0.26	0.78	0.34	0.19		
Final spec							-17.5100	194
point 1	2.59	0.60	0.25	1.26	0.19	0.37		
point 2	0.21	0.22	0.10	1.35	0.44	0.52		
point 3	0.45	0.13	0.39	0.96	0.13	0.05		

In all cases, the biggest relative spread in the heterogeneity terms is found in the exits from work. If we use Akaike's information criterion, which is  $AIC(C) = -2 \ln L_c + 2N_c$  (with  $C$  the number of points of support and  $N_c$  the number of parameters to be estimated), the ranking in terms of which model gives most information becomes: final model  $\succ$  Spec. 2  $\succ$  Spec. 3  $\succ$  Spec. 1. The biggest increase in likelihood occurs when we switch from 2 to 3 heterogeneity terms, whereas increased flexibility of the probability distribu-

tion delivers only marginal gains which barely make the final specification, with a 27 point probability distribution, better than specification 2 in which there are only 3 probability points. To see whether the parameters of main interest are affected by the assumption on the heterogeneity distribution, we show the found persistence effects under specification three, that is with a six-dimensional probability distribution with only two mass-points and only two points in each marginal heterogeneity distribution.

Table 5: found persistence effect in the third specification with 2 heterogeneity points per transition rate.

Variables \	State	Work		Unemployed		Non-part	
	exit-state	Unemployed	Non-part	Work	Non-part	Work	Unemployed
Persistence-effects							
ln(cum. nw duration) <sup>2</sup>		0.03	0.06	0.15**	0.23*	0.19**	0.03
cum. nw dur > 6 mnd?		0.04	-0.09	-0.08	-0.001	-0.20**	-0.05
cum nw dur > 1 jr?		-0.13	0.06	0.05	-0.11	0.08	0.30
cum nw dur > 2 jr?		-0.58**	-0.41**	-0.06	-0.13	-0.01	-0.16
cum nw dur > 3 jr?		-0.25	-0.03	0.27*	0.13	-0.22**	-0.51
ln(cum. work dur)		0.23**	0.12**	0.01	0.01	-0.02	0.22**
ln(previous non-work dur)		0.06	0.10**	-0.12**	-0.12	-0.18**	-0.09
ln(prev. work dur)		-0.21**	-0.06**	0.21**	0.09	0.03	-0.13
ln(Income prev. job)		0.09	-0.03	0.15**	-0.15	0.09**	0.07
ln(Income prev. non-work)		0.16**	-0.44**	-0.07**	-0.05	-0.10**	0.17**
ln(cum income)		-0.01	0.02	-0.09*	-0.01	0.03*	-0.002
Average Log likelihood				-17.53			
N				15660			

The results differ from those in the final specification in some respects: the persistencies for the transition of unemployment to non-participation are significantly different for this third specification<sup>2</sup>. For the transition rates from non-participation to unemployment, the results are also significantly different for this specification. For the transition from work to unemployment, we see that the duration persistencies are smaller and that the income

<sup>2</sup>Significantly different here means that we could reject at the 95% confidence level the hypothesis that the coefficients for the relevant transition rate in the final specification were the same as the coefficients found in this specification.

persistencies are stronger with this third specification. For the other transition rates, the results are not significantly different from the results of the final specification. We therefore do find evidence that it makes a difference whether one takes two or three heterogeneity points, although the shift in parameters is not dramatic.

## 4 Conclusions

With the use of administrative data on a panel of about 5000 Dutch labour market entrants over the period 1989-1997, we studied the effect of previous labour market outcomes on current transition rates. Generally speaking, we found that longer spells of well-paid employment increased future transition rates into work, indicating that these individuals pick up more skills in longer lasting well-paid jobs. Combining this with the fact that the incomes during employment were also greater for individuals with longer previous employment spells, we find an indication of a positive persistency of well-paid, long spells of employment.

The exit rates of non-employment (both unemployment and non-participation) to work generally did decrease somewhat with longer previous spells of non-employment and showed marked drops after 2 years. This finding is in line with the recent studies of Omori (1997) and Blau (1994) who also find a negative effect of longer previous spells in non-employment on transition rates into employment. On the other hand, longer non-employment spells also decreased transition rates from employment to other states. Long cumulative spells of non-employment hence seem to lead to general lethargy.

Another robust finding was that higher previous incomes in non-employment increase the future transition rate from employment to unemployment. One could interpret this as a learning effect of higher benefits in the sense that individuals with previous high benefits are more likely to leave employment in the future.

In an attempt to assess the effect of these persistencies on the population level, simulations were run in which some of the persistencies were ‘turned’ off. These simulations revealed that the income persistencies from work do not make a large difference, except perhaps for individuals between 20 to 30 years of age where these persistencies lead to higher levels of employment compared to the simulation in which these persistencies were turned off. The duration of non-employment turned out to increase employment levels,

probably because individuals with long periods without a job have much lower transition rates from work. Hence, although these simulations require a lot of caution because they require imputations of incomes and imputations of changes in personal characteristics, they do suggest that on balance the effect of longer periods of non-employment on future probabilities of being in employment is positive.

One implication for previous work of the positive persistencies related to employment spells is that analyses based on multiple non-employment spells (alternated with unobserved employment spells) alone will face the problem that individuals will have had an unobserved change in their hazard rates to employment as a result of these persistencies. The influence of these persistencies will then be partially picked up by observed factors that are correlated with the hazard rate from work and with work income.

An important omission in the analysis is an account of the endogeneity of current incomes with previous labour market outcomes and unobserved heterogeneity: ad hoc analyses in the appendix show significant relationships between incomes and previous labour market outcomes, but there were no instruments available to take a proper account of the endogeneities. It for instance seems very likely that the skills picked up in well-paid jobs that increase future exit rates into employment, will also increase future earnings in all states, which probably increases exit rates into work. Similarly, the unobserved heterogeneity with respect to the exit rates to work are bound to be related to incomes. As long as incomes are weakly endogenous, this problem does not affect the found coefficients for the transition rates. However, the endogeneity do give rise to some caution when it concerns the validity of the model simulations which do not take account of this inter-dependence.

## 5 Appendix

First, we show the found probability masses of the heterogeneity distribution of the final specification. By  $P[\lambda_1^{w \rightarrow u}, \lambda_1^{w \rightarrow o}, \lambda_1^{u \rightarrow w}, \lambda_1^{u \rightarrow o}, \lambda_1^{o \rightarrow w}, \lambda_1^{o \rightarrow u}]$ , we denote the joint probability that the individual's unobserved heterogeneity point for the transition from w to u is the first heterogeneity point, that the het. point for the transition from w to o is the first het. point, etc. For the 27 different probabilities, there holds (as in the tables, \* denotes significance at the 95% confidence level and \*\* denotes significance at the 99% level):

$$P[\lambda_1^{w \rightarrow u}, \lambda_1^{w \rightarrow o}, \lambda_1^{u \rightarrow w}, \lambda_1^{u \rightarrow o}, \lambda_1^{o \rightarrow w}, \lambda_1^{o \rightarrow u}] \approx 0.049$$



$$P[\lambda_2^{o \rightarrow w}, \lambda_2^{o \rightarrow u}] \approx 0.269^{**}$$

$$P[\lambda_3^{o \rightarrow w}, \lambda_3^{o \rightarrow u}] \approx 0.508^{**}.$$

The main item of interest is that each marginal distribution is for each marginal probability distribution, there is at least 15% probability mass for any of the points, which indicates that the population is divided into more than just two groups.

## 5.1 Simulations

In the simulations, the following steps were taken:

1. The joint distribution of age and gender at entry is set at the empirical distribution. For example, 5% of all male entrants started aged 15. On the basis of age and gender, an individual is assigned to being of a major city according to the empirical distribution (probit analysis). On the basis of age, gender, and location an individual is assigned to being someone who lives together with someone else or not (probit). On the basis of all variables thus far assigned an individual is assigned a number of children according to a direct competing-risk probit-model estimated on the whole sample (including all individuals whose entrance is not observed). Then, on the basis of a competing-risk probit-model using all assigned variables thus far, someone is assigned to be in one of the three states as initial state.
2. All individuals are assigned a vector of unobserved heterogeneity points according to the estimated probability distribution.
3. Considering all observed characteristics, an individual is assigned an income, by first specifying whether someone has a positive income or not (probit), and then, for those with positive incomes, to take a random draw of the estimated income distribution (log-normality with all characteristics as linear regressors, including previous lengths of employment and non-employment spells (set at 0 for entrants)).
4. (January 1st each simulated year). All ages are increased by one year. Whether someone lives together and the number of children are re-assigned according to an estimated competing risk probit-model using all observations, using the characteristics of the previous state as variables.

5. Each day an individual's hazard rate to the two possible exits is computed (with the personal characteristics equal to the personal characteristics at the start of the spell). Random draws determine who makes an exit.
6. If someone changes states, he is re-assigned a new income.
7. If someone reaches the age of 45, the simulation stops for that individual.

We mention that for the analysis of changes in household characteristics, we could use the whole dataset, for which we knew of all individuals at the start of a new year what the household characteristics were at that moment.

An important alternative to assigning individual characteristics was to take the current set of labour markets entrants plus their characteristics (including starting state and starting income) and their ensuing labour market outcomes as the starting base and to assign unobserved heterogeneity points using a Bayesian estimate of the individual probability distribution of the unobserved heterogeneities given the individual's actual labour market outcomes and the population distribution as a prior. In that case, we would still have needed to estimate some sub-models to update personal characteristics and incomes, but we would have had a better correspondence to the empirical distribution of initial conditions. The main reason to simulate everything was to keep maximum control over the simulation process.

Finally, the last table gives the results of the simple income model, in which we estimated  $y_i^k = I_{(\alpha x_i + v_i^k) > 0} \exp(\beta x_i + e_i^k)$ , where  $k$  denotes a particular state,  $x_i$  a vector of characteristics at the start of a spell and where  $v_i^k$  and  $e_i^k$  are assumed to be independently normally distributed. To improve efficiency and in order to allow us to simulate incomes for ages not contained in the panel of entrants, all the observations in the Income Panel are used, which changes the persistency variables we can use.

Table 6: results of income estimation

Variables	state	Work		Unemployed		non-participation	
		$\alpha$	$\beta$	$\alpha$	$\beta$	$\alpha$	$\beta$
Individual charact.							
Living together		-0.05*	0.03**	0.42*	-0.04**	0.24**	-0.02
ln(age)		1.09**	0.90**	0.64**	0.55**	-1.02**	0.73**
female		-0.11**	-0.35**	0.20	-0.14**	0.25**	-0.38**
# children		0.13**	-0.31**	0.02	0.04**	-0.05**	-0.08**
# children*female		0.02	-0.03**	-0.02	-0.12**	-0.07**	0.04**
big city		0.07**	0.05**	0.002	-0.02**	-0.14**	0.07**
Persistencies							
ln(length of previous non-empl.)		0.06**	-0.03**	0.10	-0.05**	-0.01	-0.04**
ln(income previous non-employment)		-0.07**	0.16**				
ln(income previous job)				-0.27**	0.11**	-0.14**	0.14**
ln(length prev n-e)*ever unemployed		0.08**	-0.01**	0.002	0.04**	-0.12**	0.04**
ln(length prev. job)		-0.41**	0.16**	-0.05	-0.01**	0.03**	-0.01**
ln(length prev. n-e)*#children		-0.01*	0.04**	-0.01	-0.001	0.001	0.01**
Entrant?		0.38**	-0.59**	0.45*	-0.15**	-0.18**	-0.19**
Missing info on previous states?		-0.16*	0.62**	-0.13	-0.16**	-0.56**	0.10
Log Likelihood	$\backslash R^2$	-8947.5	0.41	-152.5	0.23	-28599.9	0.18
N		83016	79327	25790	25731	56729	13915

Constants are not shown. Perhaps the most interesting finding here is that a longer previous spell of employment significantly reduces the probability of having no income the next employment spell and greatly increases the income earned in the next employment spell, which clearly suggest a positive persistency of longer employment spells. Individuals without children who were out of a job for long do have significantly lower incomes in employment. The other relationships between lengths without a job and incomes are not clear-cut.

## Referenties

1. Blau, D.M. (1994), 'Labour force dynamics of older men', *Econometrica*, vol. 62, pp. 117-156.
2. Bonnal, L., Fougere, D., Serandon, A. (1997), 'Evaluating the impact of french employment policies on individual labour market histories',



*Review of Economic Studies*, 64, pp. 683-713.

3. Cross, R. (1995), *The natural rate of unemployment. Reflections on 25 years of the hypothesis*. Cambridge University Press, Cambridge.
4. Dustmann, C., Meghir, C. (1999), 'Wages, experience and seniority', *CEPR-discussion paper* 2077.
5. Frijters, P., Lindeboom, M., Van den Berg, G. (1999), 'Herhalingswerkloosheid: persistenties op de arbeidsmarkt', report for the ministry of Social Affairs, Staatsdrukkerij: Den Haag. *To appear shortly*.
6. Gritz, R.M. (1993), 'The impact of training on the frequency and duration of unemployment', *Journal of Econometrics*, pp. 21-51.
7. Ham, T., Lalonde, R.J. (1996), 'The effect of sample selection and initial conditions in duration models', *Econometrica*, 64, pp. 175-205.
8. Heckman, J.J., Borjas, G. (1980), 'Does unemployment cause future unemployment?', *Economica*, pp. 247-283.
9. Heckman, J.J., Singer, B. (1984), 'A method for minimizing the impact of distributional assumptions in econometric models for duration data', *Econometrica*, 52, pp. 271-320.
10. Heckman, J.J., Walker, J.R. (1990), 'The Relationship between Wages and Income and the Timing and Spacing of Births: Evidence from Swedish Longitudinal Data', *Econometrica* 58(6), pp. 1411-41.
11. Helson, H. (1964), *Adaptation-level theory: an experimental and systematic approach to behaviour*, Harper & Row: New York.
12. Honoré, B.E. (1993), 'Identification results for duration models with multiple spells', *Review of Economic Studies*, 60, pp. 241-246.
13. Lindbeck, A. (1995), 'Hazardous welfare state dynamics', *American Economic Review*, 85, Papers and Proceedings, 9-15.
14. Ljungqvist, L., Sargent, T.J. (1998), 'The European unemployment dilemma', *Journal of Political Economy*, vol. 106(3), pp. 514-50.

15. Lockwood, B. (1991), 'Information externalities in the labour market and the duration of unemployment', *Review of Economic Studies*, pp. 733-753.
16. Lynch, L.M. (1985), 'State dependence in youth unemployment: a lost generation?', *Journal of Econometrics*, pp. 71-84
17. Lynch, L.M. (1989), 'The youth labour market in the eighties: determinants of re-employment probabilities for young men and women', *Review of Economic Studies*, pp. 37-45.
18. Mealli, F., Pudney, S. (1996), 'Occupational Pensions and Job Mobility in Britain: Estimation of a Random-Effects Competing Risks Model', *Journal of Applied Econometrics*, 11(3), pp. 293-320.
19. Omori, Y. (1997), 'Stigma effects of nonemployment', *Economic Enquiry*, 35, pp. 394-416
20. Phelps, E. (1972), *Inflation policy and unemployment theory: the cost benefit approach to monetary planning*. London, McMillan.
21. Piore, M.J. (1971), 'The dual labour market: theory and implications', in *Problems in Political Economy: an urban perspective*, Gordon, D. (ed.), Lexington Mass: Lexington books, pp. 93-97
22. Ridder, G. (1986), 'An event history approach to the evaluation of training, recruitment and employment programs', *Journal of Applied Econometrics*, 1, pp. 109-126.
23. Ridder, G. (1990), 'The non-parametric identification of generalised accelerated failure-time models', *Review of Economic Studies*, 57, pp. 167-82.
24. Roed, K. (1997), 'Hysteresis in unemployment', *Journal of Economic Surveys*, 11(4), pp. 389-418.
25. Trivedi, P.K., Alexander, J.N. (1989), 'Reemployment probability and multiple unemployment spells: a partial likelihood approach', *Journal of Business and Economic Statistics*, pp. 395-401.

26. Van den Berg, G.J., Lindeboom, M. (1998), 'Attrition in Panel Survey Data and the Estimation of Multi-state Labor Market Models', *Journal of Human Resources*, 33(2), pp. 458-78.