Discussion Paper

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No. 52 18. oktober 1990

Non-Stationary Inflow and Duration of Unemployment

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Abstract

This paper is concerned with econometric problems and methods involved in estimating duration models using data on incomplete unemployment spells provided by standard labor force surveys. In particular it considers how the model estimates are affected by the commonly applied assumption of stationary inflow rates, also in models which account for the effect of unobserved heterogeneity.

*This work was partly supported by the Norwegian Council for Science and the Humanities.

1 Introduction

Econometric work using models for the analysis of duration data has recently attracted much attention, both from econometric theorists and from applied researchers. In the literature it has particularly been focused on the specification and estimation of models for the duration of unemployment, see, for example, Lancaster (1979), Lancaster and Nickell (1980) and Narendranathan, Nickell and Stern (1985). The approaches used in these analysis are of the reduced form type founded on the economic theory of job search. Search theory is used for interpreting the estimated model parameters. There is, however, also an extensive literature on the structural form approach which is surveyed in Devine and Kiefer (1987).

The purpose of this paper is to examine various methodological approaches for estimating reduced form models from data on uncompleted spells of unemployment. The individual duration data comes from the quarterly Norwegian Labor Force Survey. This survey is conducted in a similar way as the Census Bureau's monthly Current Population Survey (CPS) and collects information on interrupted spells of unemployment only for those individuals unemployed at the survey date. The CPS interviews individuals at one point in time in each month about their current labor market status and length of unemployment for those individuals unemployed at the time of the survey. The resulting gross flow data are used to produce exit probabilities grouped into duration categories at 4-week intervals. Accordingly, CPS reporting technique introduce measurement errors into the reported unemployment durations. The special problems associated with this type of observation plans and reporting techniques are discussed in Kiefer et al. (1985). The conclusion of that paper is that "the best inferences that can be made about unemployment durations by using CPS-like data are seriously biased." The arguments of Kiefer et al. (1985) are based on a study where a sample of completed unemployment spells obtained from panel data is available. Moreover they applied CPS sampling and replicated CPS type of data. Comparison of the estimated models based on grouped gross flow versions of CPS-like data and data of completed unemployment spells, respectively, disclosed important discrepancies in parameter estimates. The results demostrated that the mean durations and the frequency of long spells were considerably underestimated.

As opposed to the study of Kiefer et al. (1985) we base our study on individual data on uncompleted spells which also in principle is available from the CPS. Consequently, we avoid the measurement errors introduced by the CPS reporting technique.

A common approach for estimating the distribution of completed unemployment durations using data on uncompleted spells of unemployment is to assume stationary inflow rates. Based on additional data on monthly inflow rates, we have examined the effect of an incorrect stationarity assumption on the estimated duration models. Specifically, we have studied the influence of the stationary assumption on estimation of duration models in the presence of unobserved heterogeneity. Unobserved heterogeneity is due to incomplete exogenous information in the data because some relevant variables are unobservable.

Our results indicate that the conclusion of Kiefer et al. (1985) has to be modified. The problems arising from applying the reported CPS data seem to originate merely from the CPS reporting technique and not from the CPS sampling technique. However as for Kiefer et al. our findings are specific to the data set used.

2 Model specification

In this paper we apply hazard function models for studying unemployment durations. Then the key quantity is the hazard function of reemployment, i.e. the conditional probability (intensity) of leaving unemployment given the duration of the spell. Within the search theory framework this conditional probability can be interpreted as the product of the probability of receiving a job offer and the probability of accepting this offer. The latter probability is a function of the preferences of the unemployed individual and his wage offer distribution and will therefore depend both on personal characteristics such as age and education and environmental influences such as availability of jobs. The probability of receiving a job offer varies between individuals because of variation in expected productivity and local labor demand and will therefore depend on the same variables. Hence, for distinguishing the effects of various variables on the probability of receiving and accepting a job offer, respectively, one has to employ a structural model. However, lack of relevant wage data makes it impossible for us to estimate a structural model. Our study is therefore confined to reduced form models, which means that job search theory only is adopted to interpret the model parameters. As a consequence few a priori assumptions about the mechanism governing the distribution of wage offers and the behavior of the unemployed job seekers need to be imposed on the econometric model.

Suppose that the duration of a completed unemployment spell is a random variable T with distribution function $F(\cdot)$ and density $f(\cdot)$. Then the probability of leaving unemployment during a short interval $[t, t+dt\rangle$, given that the duration is longer or equal to t, is given by

$$\theta(t)\,dt \;\equiv\; Pr(t \leq T < t+dt \mid T \geq t) \;=\; \frac{f(t)\,dt}{1-F(t)}. \tag{1}$$

According to (1) we have that

$$F(t) = 1 - \exp(-\int_0^t \theta(u)\,du) \tag{2}$$

which shows that there is one a to one correspondence between $f(\cdot)$ and $\theta(\cdot)$.

The specification of $\theta(\cdot)$ is concerned with functional forms for the time dependence and the description of how $\theta(\cdot)$ varies between individuals. According to the discussion above, the variation of $\theta(\cdot)$ depends on both personal characteristics and demand side effects. However, in practical applications only some of the relevant variables will usually be observerved, so that important heterogeneity will remain unexplained. As is well known, failure to adequately control for unobservables can produce severe bias in the parameter estimates for the included explanatory variables as well as create a misleading impression of duration dependence. The standard approach of controlling for unobserved heterogeneity is to assume a functional form for the hazard function given observed and unobserved explanatory variables, and a functional form for the distribution of unobservables, see, e.g. Heckman and Willis (1977) and Lancaster (1979). In the present study we apply a more flexible procedure proposed by Heckman and Singer (1982, 1984), where the distribution of unobservables is approximated by a multinomial distribution. Then the estimation problem consists of fitting mixing densities to data.

Our basic specification is the proportional hazard family of models for single spell data assuming time invariant explanatory variables. Within this family the hazard function is assumed to be on the form

$$\log\theta(t \mid x, v) = \log\psi(t) + \beta x + v \tag{3}$$

where $\psi(\cdot)$ is a baseline hazard, x is vector of explanatory variables and v is a variable that summarize the effect of the omitted variables. Note that the heterogeneity component v is supposed to be independent of t and x.

The family (3) is particular attractive since it includes models with and without duration dependence, and with and without controlling for the effect of unobserved heterogeneity.

According to (2) and (3) the duration distribution that corresponds to (3) is given by

$$F(t \mid x, v) = 1 - \exp(-e^{\beta x + \log v} \int_0^t \psi(u)\, du). \tag{4}$$

In the present study the baseline hazard $\psi(\cdot)$ is assumed to be on the following form

$$\psi(t) = \alpha t^{\alpha - 1} \tag{5}$$

which means that the model exhibits positive, negative or no duration dependence depending on whether $\alpha > 1, \alpha < 1$ or $\alpha = 1$, respectively.

The distribution of unobservables, $K(\cdot)$, is assumed to be on the two following forms,

$$dK(v) = [(\sigma^2)^{-\sigma^2} / \Gamma(\sigma^{-2})] v^{\sigma^{-2}-1} e^{-\sigma^{-2} v}\, dv \tag{6}$$

and

$$dK(v) = q_i \quad \text{for } i = 1, 2, \ldots, r, \; q_i \geq 0, \; \sum_{i=1}^{r} q_i = 1. \tag{7}$$

Consequently, the unobservables are assumed to follow a gamma or a multinomial distribution.

In this study the following models are estimated,

1. No duration dependence (ψ=1) and no control for unobservables (v=1)

2. Duration dependence specified as in (5) and no control for unobservables (v=1)

3. No duration dependence (ψ=1) and control for unobservables according to (2)

4. Duration dependence specified as in (5) and control for unobservables according to (2)

5. No duration dependence (ψ=1) and control for unobservables according to (7)

6. Duration dependence specified as in (5) and control for unobservables according to (7).

Given a constant baseline hazard the multinomial case provides the following duration distribution, conditional on membership in subpopulation i,

$$F_i(t \mid x) = 1 - \exp(-te^{\beta_{oi}+\beta x}) \tag{8}$$

Therefore, the observable distribution $F(\cdot \mid x)$ is a mixture of exponential distributions,

$$F(t \mid x) = \sum_{i=1}^{r} q_i[1 - \exp(-te^{\beta_{oi}+\beta x})] \tag{9}$$

If we alternatively assume gamma distributed unobservables and a baseline hazard given by (5) the observable distribution $F(\cdot \mid x)$ is given by

$$F(t \mid x) = \int_0^\infty F(t \mid x, v)\, dK(v) = 1 - (1 + \sigma^2 t^\alpha e^{\beta x})^{-\sigma^{-2}}. \tag{10}$$

This distribution emerges by integration provided that $F(\cdot \mid x, v), \psi(\cdot)$ and $K(\cdot)$ are given by (4), (5) and (6), respectively.

3 Data and likelihood function

In order to estimate the models (9) and (10) we need data on individual unemployment durations and on relevant explanatory variables. The most informative data are those which provide completed durations of unemployment. In this case the likelihood function is simply equal to the product of the theoretical densities given by the corresponding density functions of either (9) or (10).

The standard labor force surveys, however, provide merely data on incomplete spells of unemployment on those individuals unemployed at the time of the survey. The Norwegian Labor Force Survey, of which our study is based, is a quarterly sample survey[1] with incomplete data on individual unemployment durations.

In order to estimate the distribution of completed unemployment durations, we therefore have to express the distribution of observed incomplete unemployed spells in terms of the distribution of complete unemployment spells.

Now, consider an individual who is unemployed at the interview date s_0 of the survey. Let $k(s)$ denote the inflow rate into unemployment at time s, i.e. the proportion of the population that enters unemployment at s. Further, let $F_s(\cdot)$ denote the distribution of the length of unemployment if the unemployment spell starts at date s. Then the density of the observed elapsed duration at time s_0 of the survey is

$$g(t) = \frac{k(s_0 - t)(1 - F_s(t))}{\int_{-\infty}^{s_0} k(s)(1 - F_s(s_0 - s))\, ds}. \tag{11}$$

The nominator of $g(t)$ is equal to the simultaneous probability that an individual is entering the unemployment state at date $s_0 - t$ and is still unemployed at date s_0, which means that the length of the observed incomplete unemployment spell is equal to t. The denominator of $g(t)$ is equal to the probability of being unemployed at date s_0. Thus, (11) is the ratio of the expected number of favorable to the expected number of possible events.

According to (11), the density of the observed incomplete spells depends on the previous history of the process. However, lack of individual time series data makes it necessary to impose restrictions on the general form of (11). If the entry rates, $k(\cdot)$, are known and cross-sectional duration data is available, then it is possible to identify the distribution of completed durations provided that the distribution is a member of a parametric family and is independent of the calender time. In the present paper we compare this approach, called the synthetic cohort method, with the more common method of assuming stationary entry rates into unemployment. The stationarity assumption leads to the following simple version of (11)

[1] As from 2nd quarter 1988 the data are collected monthly.

$$g(t) = \frac{1 - F(t)}{\mu} \tag{12}$$

where

$$\mu = \int_0^\infty (1 - F(t))\, dt. \tag{13}$$

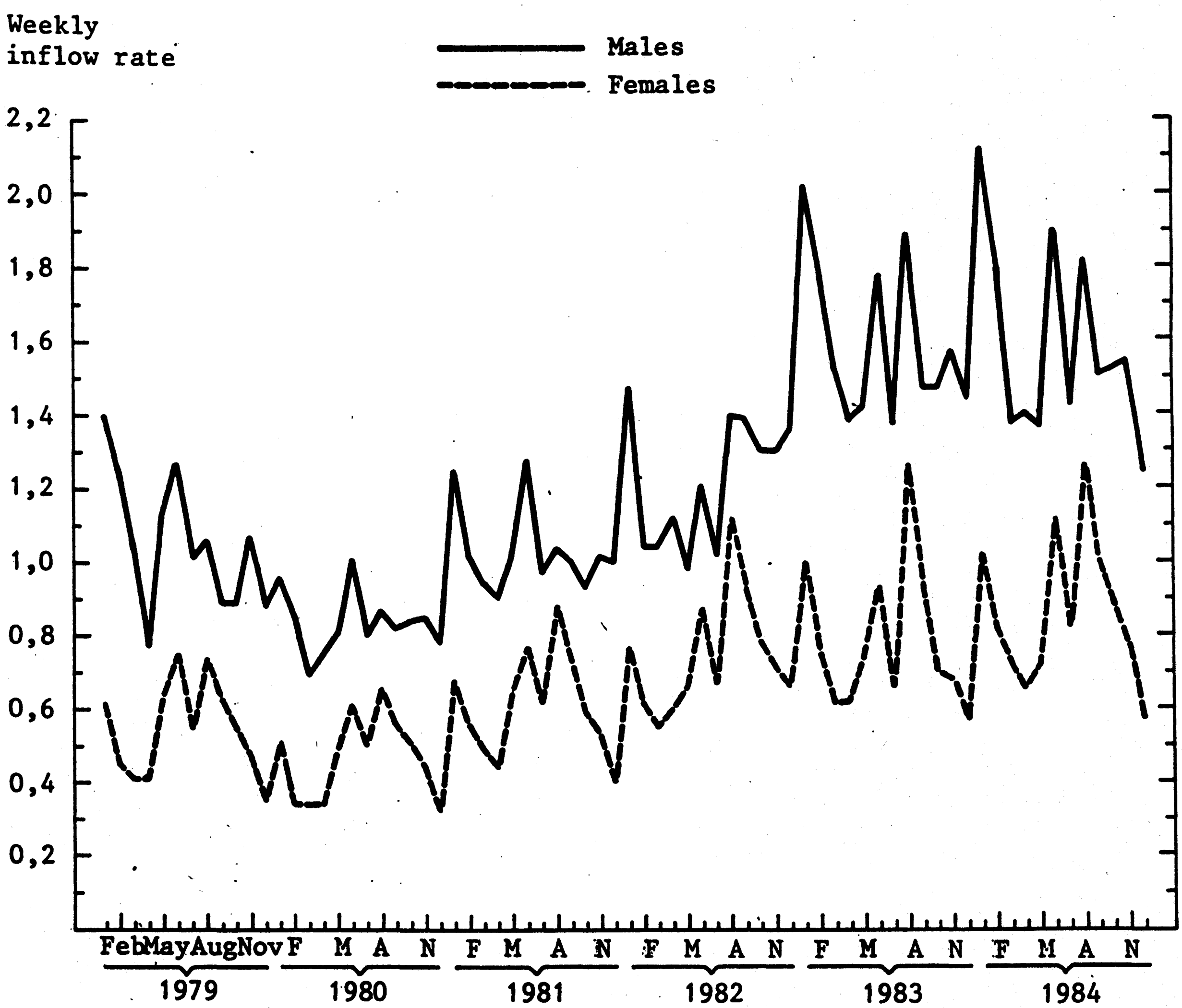
We have considered five parametric families for F. One is given by (9) and the remaining four emerge from (10) as α and/or σ^2 are specified equal to *1* or *0*, respectively.

The Norwegian Labor Force Survey identifies two types of spells:

(i) incomplete unemployment spells, i.e. the length of time spent in unemployment until the date of the survey, and

(ii) censored incomplete unemployment spells at 99 weeks, i.e. the length of the elapsed duration at the date of the survey is 99 weeks or more.

Figure 1. Weekly inflow rates[2] to unemployment for females and males



[2]Weekly inflow rate for females (males) = $100 \cdot \frac{\text{Weekly inflow for females (males)}}{\text{Number of femles (males) at ages 16–74 years}}$

The contribution of each type of spell to the likelihood function is $g(t)$ and $1\text{-}G(99)$, respectively, where G is the distribution function of the observed elapsed durations at the date s_0 of the survey.

Application of the synthetic cohort method requires known flows into unemployment. In Norway only monthly figures for males and females registered as new applicants for work at the Employment and Seamen's Offices are available. The fraction of applicants for work without paid job is, however, supposed stable during each year. This fraction is registered for January every year and form the basis of the derivation of the monthly entry rates into unemployment. Moreover, the weekly entry rates shown in Figure 1 are based on the additional assumption of constant rates within each month. The monthly number of new applicants for work varies in 1979-1984 between 15 000 and 30 000 for males and 6 000 and 19 000 for females, while the fraction without paid job varies between 0.4 and 0.5. Figure 1 demonstrates that the weekly inflow rates vary with season and that they are larger in 1983-1984 than in 1979-1982.

Now, let us consider the variables that may affect the duration of a spell of unemployment, i.e. the variables that may affect the probabilities of receiving and accepting a job offer, respectively. The probability of receiving a job offer is influenced by the local labor demand and the job-specific human capital of the unemployed job-seekers. The probability of accepting a received job offer depends on job characteristics such as wage, worker rules, safety and environmental conditions, on other income such as benefits, cost of search and on motivation and preferences for leisure. The explanatory variables used in this study are length of education and local unemployment rates for males and females, respectively. To obtain an elasticity interpretation of the β coefficients we have applied the following specification

$$\beta x = \beta_0 + \beta_1 \log \text{ Education } + \beta_2 \log \text{ Unemployment.} \tag{14}$$

The above discussion suggests that these two explanatory variables do not represent the complete set of regressors. Thus, it is necessary to control for the effect of omitting other relevant explanatory variables. This is the reason why we estimate alternative models with and without control for unobservables.

Now, suppose a random sample of r individuals is selected from the stock of unemployed persons at the date of the survey. If individuals $i = 1, 2, \ldots, n_1$

at the date of the survey have been unemployed for t_i weeks, where each t_i is assumed to be less than 99 weeks, and the remaining $n_2(= n - n_1)$ individuals have been unemployed for 99 weeks or more the likelihood function is

$$\mathcal{L} = \prod_{i=1}^{n_1} g(t_i \mid x_i) \prod_{j=1}^{n_2} (1 - G(99 \mid x_j)) \tag{15}$$

where $g(t \mid x)$ and $G(t \mid x)$ are related to the distribution $F(t \mid x)$ of completed unemployment spells through (11) or (12), and $F(t \mid x)$ is assumed to be a member of the parametric families (9) or (10). This leads to the following expressions for $g(t \mid x)$:

If $F(\cdot \mid x)$ is given by (10), then

$$g(t \mid x) = \frac{k(s_0 - t)(1 + \sigma^2 t^\alpha e^{\beta x})^{-\sigma^{-2}}}{\int_0^\infty k(s_0 - s)(1 + \sigma^2 s^\alpha e^{\beta x})^{-\sigma^{-2}}\, ds} \tag{16}$$

which under the assumption of stationary entry rates reduces to

$$g(t \mid x) = e^{\beta x}(1 - \sigma^2)(1 + \sigma^2 t e^{\beta x})^{-\sigma^{-2}}. \tag{17}$$

If alternatively $F(\cdot \mid x)$ is specified according to (9), then

$$g(t \mid x) = \frac{k(s_0 - t) \sum_{i=1}^{r} [q_i \exp(-t e^{\beta_{oi} + \beta x})]}{\sum_{i=1}^{r} q_i \int_0^\infty k(s_0 - s) \exp(-s e^{\beta_{oi} + \beta x})\, ds} \tag{18}$$

which when $k(s_0 - s)$ is constant reduces to

$$g(t \mid x) = \frac{\sum_{i=1}^{r} q_i \exp(-t e^{\beta_{oi} + \beta x})}{\sum_{i=1}^{r} q_i e^{\beta_{oi} + \beta x}}. \tag{19}$$

Note that our application of the aggregated inflow data is in accordance with the specifications ((16)-(19)) where we assume that the "individual" inflow rates $k(\cdot \mid x)$ follow a multiplicative structure,

$$k(t \mid x) = k(t) \cdot b(x). \tag{20}$$

For normalizing purposes we choose $\beta_{0r} = 0$ in (18) and (19). This is necessary since βx includes a constant term.

4 Results

In the specification of the models we have emphasized the importance of flexible functional forms with respect to gender and age. Consequently, we have estimated separate models for females and males in age groups 20-29 years and 30-49 years, respectively. The arguments are that the effect of length of education on the productivity varies with age and that the effect of local demand on the probability of obtaining a job varies with gender and age.

For each subgroup we have estimated six alternative models which are numbered from 1 to 6 in section 2. The results are presented in Tables 1-4.

The first and most important point to note about the results in Tables 1-4 is that the incorrect assumption of stationary inflow rates (see Figure 1) does not significantly affect the parameter estimates. Thus, the following statement in Kiefer et al. (1985), "even relatively minor departures from stationary inflows can have large consequences for the estimates", evidently finds no support in our results.

The parameter estimates indicate that the effect of length of schooling is more important for individuals at ages 20-29 years than for individuals at ages 30-49 years. The coefficient estimates on schooling are highly significant and only modestly affected by the choice of functional form except for males at ages 20-29 years. This robustness property is also present for the coefficient estimates on the gender specific local unemployment rates. However, these parameter estimates are on the other hand hardly significant.

According to the arguments in Section 2 it is most important to control for the presence of unobserved heterogeneity. The models 3 and 4 include Gamma distributed unobservables while the models 5 and 6 account for heterogeneity through the specification of mixtures of exponential and Weibull distributions, respectively. The values of $-2\log L$ confirm the importance of including heterogeneity. According to the likelihood ratio test the exponential model with Gamma distributed heterogeneity appears to fit the data best for both females and males at ages 30-49 years. For females and males at ages 20-29 years the mixtures of exponential and Weibull distributions, respectively, fit the data best. For males at ages 20-29 years there are evidence in favor of positive duration dependence, which is in accordance with the declining reservation wage hypothesis. On the other hand model 2, which does not control for the effect of unobservables, indicate negative duration dependence. However, according to Heckman and Singer (1982) observed negative duration dependence often occurs even when the structural hazard is positive. This is so due to of the effect of unobserved heterogeneity. For this specific age group also note that the parameter estimate associated to length of schooling is considerably larger for model 6 than for the alternative models.

Table 1: Maximum likelihood estimates[1] for alternative duration models. Females at ages 20-29 years

Model	*Inflow*	β_0		β_1	β_2	α	σ^2	q_1	$-2\log L$
1	S	-9.70		2.39	-0.29	-	-	-	2041.1
		(1.12)		(0.49)	(0.12)				
	NS	-10.04		2.47	-0.32	-	-	-	2048.4
		(1.15)		(0.50)	(0.13)				
2	S	-6.75		1.83	-0.18	0.73	-	-	2031.2
	NS	-7.24		1.94	-0.21	0.74	-	-	2040.1
3	S	-9.46		2.65	-0.20	-	0.21	-	2024.0
		(1.28)		(0.57)	(0.15)		(0.05)		
	NS	-9.86		2.74	-0.24	-	0.22	-	2032.8
		(1.31)		(0.58)	(0.15)		(0.06)		
4	S	-19.25		5.38	-0.33	1.97	0.71	-	2018.0
	NS	-22.20		6.15	-0.42	2.22	0.87	-	2025.1
		β_0	β_{01}						
5	S	-9.94	-3.59	2.79	-0.16	-	-	0.001	2013.8
	NS	-10.15	-3.93	2.82	-0.19	-	-	0.001	2021.8
6	S	-10.70	-3.86	2.98	-0.18	1.07	-	0.001	2013.5
	NS	-11.32	-4.38	3.10	-0.21	1.11	-	0.001	2021.2

1) The estimates are based on 271 observations. Standard deviations are given in paranthesis.
S = stationary inflow.
NS = non-stationary inflow.

Table 2: Maximum likelihood estimates[1] for alternative duration models. Females at ages 30-49 years

Model	*Inflow*	β_0		β_1	β_2	α	σ^2	q_1	$-2\log L$
1	S	-7.52		1.33	-0.30	-	-	-	1769.9
		1.05		(0.43)	(0.14)				
	NS	-7.78		1.39	-0.32	-	-	-	1776.4
		(1.11)		(0.44)	(0.15)				
2	S	-5.75		1.05	-0.24	0.81	-	-	1767.3
	NS	-5.99		1.11	-0.25	0.81	-	-	1774.0
3	S	-6.90		1.22	-0.30	-	0.16	-	1766.0
		(1.22)		(0.49)	(0.16)		(0.07)		
	NS	-7.12		1.28	-0.31	-	0.17	-	1772.7
		(1.30)		(0.52)	(0.17)		(0.08)		
4	S	-8.89		1.51	-0.38	1.30	0.34	-	1765.4
	NS	-9.48		1.63	-0.40	1.36	0.41	-	1771.9
		β_0	β_{01}						
5	S	-6.93	-3.53	1.07	-0.34	-	-	0.001	1765.0
	NS	-7.16	-3.84	1.12	-0.35	-	-	0.001	1771.7
6	S	-6.83	-3.47	1.06	-0.34	0.99	-	0.001	1765.0
	NS	-7.11	-3.81	1.11	-0.35	0.99	-	0.001	1771.7

1) The estimates are based on 220 observations. Standard deviations are given in paranthesis.

S = stationary inflow.

NS = non-stationary inflow.

Table 3: Maximum likelihood estimates[1] for alternative duration models. Males at ages 20-29 years

Model	*Inflow*	β_0		β_1	β_2	α	σ^2	q_1	$-2\log L$
1	S	-9.22		2.26	-0.29	-	-	-	2141.3
		(1.18)		(0.48)	(0.16)				
	NS	-9.73		2.42	-0.31	-	-	-	2139.5
		(1.23)		(0.50)	(0.17)				
2	S	-7.42		1.90	-0.24	0.82	-	-	2137.8
	NS	-7.87		2.04	-0.26	0.82	-	-	2136.3
3	S	-9.12		2.31	-0.31	-	0.12	-	2137.5
		(1.31)		(0.55)	(0.18)		(0.06)		
	NS	-9.67		2.49	-0.32	-	0.14	-	2135.7
		(1.39)		(0.58)	(0.20)		(0.07)		
4	S	-8.86		2.24	-0.30	0.97	0.11	-	2137.5
	NS	-9.95		2.56	-0.34	1.03	0.16	-	2135.7
		β_0	β_{01}						
5	S	-8.55	-1.04	2.34	-0.27	-	-	0.42	2135.8
		(1.44)	(0.30)	(0.55)	(0.18)			(0.18)	
	NS	-9.21	-1.06	2.55	-0.30	-	-	0.41	2134.2
		(1.52)	(0.30)	(0.58)	(0.19)			(0.19)	
6	S	-17.29	-3.02	4.74	-0.38	1.99	-	0.19	2127.9
	NS	-20.13	-3.36	5.62	-0.46	2.14	-	0.19	2125.5

1) The estimates are based on 274 observations. Standard deviations are given in paranthesis.
S = stationary inflow.
NS = non-stationary inflow.

Table 4: Maximum likelihood estimates[1] for alternative duration models.
Males aged 30-49 years

Model	Inflow	β_0	β_{01}	β_1	β_2	α	σ^2	q_1	$-2\log L$
1	S	-6.25		1.40	0.06	-	-	-	1965.5
		(1.18)		(0.48)	(0.15)				
	NS	-6.67		1.58	0.08	-	-	-	1962.2
		(1.26)		(0.51)	(0.17)				
2	S	-4.36		1.03	0.03	0.76	-	-	1959.8
	NS	-4.61		1.15	0.05	0.75	-	-	1956.6
3	S	-5.65		1.29	0.03	-	0.19	-	1957.7
		(1.42)		(0.55)	(0.18)		(0.06)		
	NS	-5.99		1.44	0.05	-	0.22	-	1954.3
		(1.55)		(0.60)	(0.20)		(0.07)		
4	S	-6.96		1.55	0.04	1.23	0.34	-	1957.3
	NS	-7.70		1.80	0.06	1.30	0.42	-	1953.6
		β_0	β_{01}						
5	S	-5.58	-1.00	1.31	0.03	-	-	0.23	1958.0
		(1.43)	(0.23)	(0.56)	(0.18)			(0.33)	
	NS	-5.94	-1.09	1.47	0.05	-	-	0.22	1954.3
		(1.54)	(0.23)	(0.62)	(0.20)			(0.27)	
6	S	-7.53	-1.76	1.78	0.03	1.33	-	0.24	1957.3
	NS	-8.64	-2.00	2.18	0.06	1.41	-	0.23	1953.3

1) The estimates are based on 245 observations. Standard deviations are given in paranthesis.
S = stationary inflow.
NS = non-stationary inflow.

References

Devine, T. J. and N. M. Kiefer (1987): "Empirical Labor Economics in the Search Framework", Mimeo, Cornell Univercity.

Heckman, J. and R. Willis (1977): "A Beta Logistic Model for the Analysis of Sequential Labor Force Participation of Married Women", Journal of Political Economy, 85, 27-58.

Heckman, J. and B. Singer (1982): "The Identification Problem in Econometric Models for Devation Data", In: Advances in Econometrics, W. Hildenbrand (eds.), Cambridge Univercity Press, 39-77.

Heckman, J. and B. Singer (1984): "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data", Econometrica, Nol. 52, No. 2.

Kiefer, N. M., Lundberg, S. and G. R. Neumann (1985): "How Long is a Spell of Unemployment", J. Bus. Econ. Statist., 3(2), 118-128.

Lancaster, T. (1979): "Econometric Methods for the Duration of Unemployment". Econometrica, Vol. 47, No. 4, 939-956.

Lancaster, T. and S. Nickell (1980): "The Analysis of Re-employment Probabilities for the Unemployed". Journal of the Royal Statistical Society, A, 141-165.

Narendranathan, W., Nickell, S. J. and J. Stern (1989): "Unemployment Benefits revisited", Economic Journal, 95, 307-29.

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